Project 7708 understanding heritage crime in Kent and Medway – a data analytical approach

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FINAL REPORT

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1 Introduction

Historic England Project 7708 'Understanding heritage crime in Kent and Medway – a data analytical approach' aims to use data analysis techniques to gain a better spatial and temporal understanding of heritage crime in Kent and Medway[1] and in so doing provide a sounder basis for the prevention of such crime.

It is envisaged that the outcomes for Kent and Medway may provide a model for similar research to be conducted elsewhere in England.

The project was in support of the Historic England 2017 Research Agenda, and in particular, the Agenda theme of '#adapt' (subheading 'Heritage crime').

This project sought to answer specific research questions posed by Historic England:

- Where are the different types of crime that affect the historic environment occurring, and how often?
- What is the particular nature of heritage crime in declining urban, rural or coastal areas?' (Historic England, 2016, p.31).

The project also linked to one of the National Police Chief Council's five distinct areas for improvement and development, namely 'assessment and analysis of intelligence and recorded crime and incident data' (NPCC, 2017, p.6).

In order to better understand heritage crime in Kent and Medway we employed a methodology that utilised both location and crime data. Methods included the overlaying of crime locations over heritage sites, testing for differences, random sampling, time series analysis and developing machine learning algorithms.

However, at the outset is important to note that our analysis looked only at heritage crime that is both tangible and relates to space and time. We did not look, for example, at e-enabled (e.g. trading in illicit heritage objects) or e-dependent (e.g. DDoS attacks which destroy archives of cultural memory) heritage crime that occurs online. These crimes have little association with location.

Our focus was exclusively Kent and Medway, the combined geographical areas covered by Kent Police. Naturally, in terms of crime, Kent and Medway will be typical of many other areas of England and Wales in some ways and less typical in others.

Table 1 below illustrates how far Kent and Medway conform to the 'norm' for England and Wales[2] and how far they differ, according to some of the most frequently occurring crime groups (where 100% is the average).

Crime category	**Proportion of national average**
Antisocial behaviour	68%
Bicycle theft	66%
Burglary	83%
Criminal damage and arson	116%

[1] By Kent and Medway we mean the geographical areas administered by Kent County Council and Medway Unitary Authority.

[2] Note that no comparison is currently possible for specifically 'heritage crime' between Kent and the rest of England and Wales.

‘Drugs’	62%
Other crime	148%
Other theft	96%
Possession of weapons	80%
Public order	131%
Robbery	62%
‘Shoplifting’	99%
Theft from the person	35%
Vehicle crime	84%
Violence and sexual offences[3]	13%

Table 1 Crimes in Kent and Medway as a proportion of national average, 2015-2018 (derived from Doherty, 2018).

Similarly, Kent and Medway will be different in sociodemographic terms from many other parts of England and Wales and this will undoubtedly be important to bear in mind when attempting to apply the ‘lessons learned’ in this study.

A full description of the sociodemography of Kent and Medway exceeds the scope of this report. However, it is important to note that whereas the Kent Police area of responsibility covers both the county of Kent and the area administered by Medway Unitary Authority the two geographical areas have distinct differences. For example, the county of Kent is much larger than Medway, while the latter is more densely populated[4].

In the remainder of this report we examine how heritage crime is defined and the legislation that surrounds it (section 2); we review the existing literature regarding previous attempts to measure the extent of heritage crime (section 3); in sections 4 and 5 we describe our data sources and the methodologies employed. The central sections of the report (6 and 7) describe the results of our analysis of the data both for Kent and Medway as a whole and three Heritage Action Zones (HAZs) within the region in particular.

During the course of the research it became apparent that there were a number of reasons why heritage crime at Places of Worship in Kent and Medway justified a more in-depth analysis, which is provided in section 8 of the report.

In section 9 we compare our results with the one previous in-depth study of the extent of heritage crime in England – what we have termed the ‘Bradley’ report.

In section 10 we employ the data we collected and collated to explore the possibility of using machine learning to forecast heritage crime, together with an illustration of its application.

We conclude the report with an overview of our research findings together with some recommendations on further research or development that Historic England may wish to consider.

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[3] Sexual offences were not included in this research.

[4] The total area covered by Kent and Medway is 3,544 km^2, of which just 192 km^2 falls under Medway Unitary Authority. However, Medway’s population density is 1,447 people per km^2, while the remainder of Kent is much lower, at 385 people per km^2.

2 Heritage Crime

There are c. 400,000 sites and buildings in England designated by Historic England as 'Heritage Assets'. Kent includes more listed buildings than any other county; according to CPRE (2019), there are c. 18,400 of these, plus several more thousand unlisted historic buildings and structures. The majority of these assets are owned and managed by members of the public.

Notable listed buildings in Kent and Medway include Canterbury Cathedral (Grade I) and Cliftonville Lido (Grade II); scheduled monuments include Richborough Roman Fort and Denge sound mirrors.

In the UK the term 'heritage crime' possibly originated in the mid to late 2000s, probably as a consequence of a growing problem with crimes such as metal theft from heritage locations and buildings (such as churches). Certainly 'heritage crime' as a distinct issue for law enforcement owes much to the role(s) played by Mark Harrison, originating during the time he was seconded as policing advisor to English Heritage (now Historic England).

Historic England currently defines 'heritage crime' as 'any offence which harms the value of heritage assets and[5] their settings' (Historic England, 2019).

Crimes against heritage locations are important to analyse, for as the Head of Heritage Crime and Policing Advice for Historic England, Mark Harrison explains, an increased level of understanding will lead to better preventative and enforcement activities (Harrison, 2018).

Examples of heritage crimes include architectural theft (particularly of metal and stone); criminal damage (e.g. graffiti on a scheduled monument); unlawful metal detecting; anti-social behaviour (most particularly off-road driving on historic sites and fly-tipping); unauthorised changes to historic buildings and the illicit trade in cultural objects. Not all of these will be recorded by the police (see section 4 later); nor can they all be meaningfully analysed in terms of time and space.

A heritage crime of particular concern is metal theft from places of worship (particularly those churches which are also listed buildings). The numbers of such crimes in Kent and Medway, their trends and association with the road network and scrap metal prices are analysed in section 8 of this report.

Grove (2013, pp.246-247) has introduced a 'heritage crime typology' which consists of 'targeted heritage crime' (heritage locations specifically criminally targeted for its heritage features); 'incidental heritage crime' (where the location happens to be a heritage site but is attractive to offenders for 'non-heritage reasons') and 'heritage-specific offences' (ones explicitly defined by law).

[5] For the purposes of this report, we assume 'and' means 'and/or' in this context.

Alternative ways of 'dividing the heritage crime cake' include ARCH's classification into 'specific heritage crime offences that apply to certain designated heritage assets' (e.g. unauthorised changes to a listed building); 'specific heritage crime offences that apply to both designated and non-designated heritage assets'(e.g. unlawful dealing in cultural objects) and 'other criminal offences which can affect heritage assets' (e.g. criminal damage to an historic building) (Historic England, 2017, p.7).

For our own purposes we have utilised the term 'Crimes Within, At or Close to Heritage Sites' ('CWACHS') in this report, as it more precisely reflects our approach. Where appropriate we have also used Grove's (2013) terms 'heritage-specific offences' and 'targeted heritage crime'.

2.1 Legislation and heritage crime

The data utilised for this study included anonymised recorded crime reports provided by Kent Police (see section 6 below).

Police crime reports cover a wide range of offences defined under legislation. Clearly there are a large number of offences which may adversely impact a historic building, location or site which, although not specific to 'heritage crime' are aggravating factors. These laws include the obvious ones such as the Theft Act 1968 and the Criminal Damage Act 1971, but also less obvious such as road traffic offences, and 'going equipped'. Most of the recorded crime that occurs at heritage locations in Kent and Medway in any given year are likely to be theft, burglary or criminal damage offences (see section 6 of this report).

There are also a number of offences defined under law which are specific to the historic environment, including listed buildings. These include the Ancient Monuments and Archaeological Areas Act 1979, Protection of Military Remains Act 1986, Planning (Listed Buildings and Conservation Areas) Act 1990, Protection of Wrecks Act 1973, Dealing in Cultural Objects (Offences) Act 2003, Treasure Act 1996, and provisions under the Town and Country Planning Act 1990. As part of our research we attempted to analyse offences of this type that occur in Kent and Medway (see section 6.1 of this report).

Under the law in England and Wales, a 'cultural object' is defined as an object of historical, architectural, or archaeological interest. It is 'tainted' if a person illegally excavates an object from its original position in the ground, or removes it from a building, structure, or monument of historical, architectural, or archaeological interest in the UK or elsewhere. Dishonest dealing of a tainted cultural object while knowing or believing it is tainted is an offence (s 1 of the Dealing in Cultural Objects (Offences) Act 2003).

'Treasure' includes old gold, silver, or bronze coins, collections of prehistoric metalwork, and objects found with such coins or metalwork (s 1 of the Treasure Act 1996). Such finds must be reported through the Portable Antiquities Scheme. It is an offence to fail to notify the district coroner within 14 days of finding 'treasure' (s 8(3) of the Treasure Act 1996).

As Grove (2013, p.242) notes, heritage crime '[...] has a greater impact on the country's legacy for future generations because of the types of sites affected'. Many of these buildings and sites of historic interest have also had some form of legal protection in the UK since 1882.

A number of bodies (local authorities, the police, and Historic England) share the responsibility to enforce legislation designed to protect heritage sites. Under the Ancient Monuments and Archaeological Areas Act 1979 (s 28) it is an offence to damage or destroy (without lawful excuse) a 'protected monument' (defined in s 28, and includes a scheduled monument).

Other sections of this Act may also be relevant: s 42, under which it is a summary offence to use a metal detector in a 'protected place' without the written consent of English Heritage; s 9, under which it is an offence to damage, demolish, or alter a listed building.

The Protection of Wrecks Act 1973 is used to designate an area containing a 'protected wreck'. Under the Act all wreck material (e.g. fixtures and fittings, coins, cannon, and wreck timbers) must be reported to the 'Receiver' at the Maritime and Coastguard Agency.

The Protection of Military Remains Act 1986 makes it an offence to interfere (without a licence) with the wreckage of any crashed, sunken, or stranded military aircraft or designated vessel. The Act provides two levels of protection, depending on whether the site is designated as a 'protected place' or a 'controlled site'. Greater restrictions are placed upon activities at the latter. Investigations under this Act usually relate to diving and are undertaken by the Ministry of Defence supported by the police and Historic England.

In 2003 the Scrap Metal Dealers Act introduced a new regulatory regime for the scrap metal dealing and vehicle dismantling industries. The 2003 Act was part of the legislative response to metal theft, which includes theft of lead and other metals from churches and other historic buildings.

2.2 Reporting and recording heritage crime

As Grove (2013, p.247) notes 'perhaps the most significant challenge facing individuals and groups attempting to research and address heritage crime is the lack of available data' and in a more recent paper she explains that this is important 'because without a baseline understanding of heritage crime, it is not possible to measure whether the problem is increasing or decreasing, nor can hotspots of illicit activity within which to direct crime prevention resources be identified' (Grove, 2018, p.2).

Project 7708 attempted to meet the challenge by accessing sanitised and anonymised recorded crime data[6] from Kent Police for the period[7] 01/01/2014 to 31/10/2018 inclusive.

An important distinction is between **reported** crime-related incidents (e.g. reports made by a member of the public to the police) and **recorded** crime.

In terms of heritage crime, a survey conducted by Bradley et al. (2012) found that approximately one in three heritage crimes had not been reported to the police (p.6).

It is also the case that a number of categories of heritage crimes include those that are hidden from view – for example, illegal metal detecting ('nighthawking') may go unrecorded if the offenders have taken care to hide their activities. Any historical objects taken would have been unknown.

Other studies have also found that heritage crimes are under-reported. For example, a heritage crime strategic assessment in 2010 undertaken by Russ Shopland, a Principal Intelligence Analyst with Kent Police, highlighted 'the under-reporting of such crimes, which in turn has an impact on prevention, intervention and prosecution' (Prescott, 2011, p.225).

The likelihood that a crime is reported to the police also varies significantly according to crime type. For example, criminal damage is widely considered to be 'underreported' (ONS, 2019, Table 1), although as our research shows this is one of the most frequently occurring crimes within or close to heritage sites in Kent and Medway.

Kent Police (in common with all police forces in England and Wales) decide whether an incident that has reported to them should then be recorded as an actual crime (a so-called 'notifiable offence').

Police decide on whether the circumstances as reported amount to an offence, based on what they know about the incident and the counting rules from the National Crime Recording Standards (NCRS) and Home Office Counting Rules (HOCR).

The police will also consider whether there is any credible evidence to the contrary. If on 'the balance of probability' the circumstances described in a report amount to an offence as defined by the law, then the incident will be recorded as a crime (Home Office, 2016).

However, in the past, HMIC (Her Majesty's Inspectorate of Constabulary), now HMICFRS (Her Majesty's Inspectorate of Constabulary and Fire & Rescue Services), have acknowledged that there is a 'degree of subjective interpretation in making

[6] Of which CWACHS forms a proportionally small subset.

[7] From its 'Athena' crime and intelligence recording system.

decisions about how to record crimes' (HMIC, 2013, p.3), and that in 2013 there was serious under-recording of crime in a number of forces, including Kent Police.

Subsequently Kent Police took a number of steps to improve its recording of crime and in 2018 were judged to be amongst the best in England (HMICFRS, 2019). Major improvements were made during the year 2017/18[8]; a period of time that coincides with our sample of data. Hence any interpretations of changes in crime rates must be viewed against these changing circumstances.

In principle, for heritage-specific crimes (that is types of heritage crime explicitly defined under legislation), data should be retrievable from police NCRS. For the purposes of this report we attempted to do this from the anonymised secondary NCRS data for Kent and Medway (see section 6.1), but the structure of the NCRS does not lend itself easily to searching for offences by legislation.

Perhaps even more fundamentally, there is '[...] the problem of data and the common lack of a heritage crime category when police are recording the crimes' (Kerr, 2017, p.678)[9]. There is currently no specific heading in the NCRS for heritage-specific offences or targeted heritage crimes. Instead, heritage crime reports are likely to be 'buried' deep within more general offence categories.

For example, the crime of 'nighthawking' is most likely to be recorded under the offence heading of 'theft -other'[10] and hence not easily identifiable amongst the large numbers of these crimes.

Kent Police, in common with all other police forces, adopted the NCRS in 2002 (Kent Police, 2016). Certain recorded crimes are 'flagged' on the NCRS; these include Hate Crime, Domestic Abuse, Online Crime and Child Sexual Abuse (Home Office, 2019). 'Metal Theft' is one of the flagged crimes and we were able to use this fact in some of our research (see section 8.1 in this report).

However, there is no Home Office requirement for police forces to flag 'heritage crime' on their crime recording systems. Although a number of police forces appear to be trialling the use of a flag for targeted heritage crimes at the time of writing (2020), this did not include Kent Police.

Hence, in most cases the only available means to determine whether a crime at, for example, a listed building is a targeted heritage crime is by inspection of the detailed crime reports associated with the NCRS record. For reasons of privacy and confidentially such inspections can only be undertaken by police service employees.

[8] In 2017 Kent Police were still being judged by HMICFRS as being 'inadequate' in terms of the force's Crime Data Integrity (HMICFRS, 2018).
[9] However, in 2018 seven police forces in England began trials of the 'tagging' of heritage crimes on their crime and intelligence recording systems.
[10] In terms of 'nighthawking' there is no ability to search the NCRS for offences under sections 42(1) and (5)(a) of the Ancient Monuments and Archaeological Areas Act 1979.

Daubney and Nicholas (2019) examined the correspondence between official (police) sources of data and unofficial (e.g. 'hobbyist') ones and concluded that:

> 'Although there are some synergies between the unofficial and official sources, the lack of detail in any one dataset makes them of limited use in demonstrating trends in the macro- and micro-scales of time and place. Accordingly, many of the issues […] could be resolved by devising a better system for police record keeping of metal detecting offences' (p.139).

Our own experience, when conducting the original research required for this report, supports extending Daubney and Nicholas' (2019) observation to the recording of targeted and heritage-specific crime in Kent and Medway.

3 Review of existing literature on the extent and distribution of heritage crime

In this section we review the existing literature on the extent of heritage crime and how it is spatially and temporally distributed.

However, as noted in section 2 of this report, reporting and recording issues make a review of the existing literature around the extent of heritage crime particularly problematic. For example, a study by Grove et al. (2018) of the sources of data on heritage crime in England and Wales found a lack of consistency in how such crimes were reported and then recorded.

Moreover, evidence of the extent of heritage crime comes predominantly from anecdotal and one-off reports, rather than any consistent reporting strategy (Grove, 2013).

Most recently, and in terms of illicit metal detecting, Daubney and Nicholas (2019) noted that '[...] lack of available data means that illicit metal detecting falls firmly into the so-called 'dark figure of crime'[11].

It is also the case that there is little, if any, published literature on the spatial and temporal distribution of heritage crime in England and Wales. However, since 2016, a more concerted effort has been undertaken to increase understanding of the prevalence and spatial distribution of heritage crime.

The objectives of 'Operation Crucible: Developing a heritage metal theft strategy' (2016) were 'to identify damage or loss to heritage assets on police and fire service call-handling and crime recording system' (p.4), 'to develop accurate and consistent reporting and recording systems and process for crime and Anti-Social Behaviour' (p.4), and 'to develop nationally agreed definitions, markers and crime recording categories' (p.6).

3.1 Extent of heritage crime

An obvious source of data on the extent of heritage crime would be statistics on recorded crime collected by police forces and then collated and published by the Home Office. However, to our knowledge no data specifically on numbers of police recorded heritage crimes has been published by a police force[12], by other law enforcement agencies (such as the National Crime Agency) or by the Home Office.

The Crime Survey for England and Wales (CSEW) is an annual survey of victimisation carried out on behalf of the Office for National Statistics. Data collected from members of the public is collated and estimates of violent crime, criminal damage

[11] Crime that does not appear in official statistics and of which we have little formal knowledge.
[12] The exceptions are a number of Freedom of Information requests to police forces concerning specific heritage crimes such as 'nighthawking'. The Home Office does publish data on 'metal thefts' but not specifically from places of worship or scheduled monuments.

and arson, computer misuse and other crimes produced and published. However, no data specifically concerned with heritage crime are provided.

Some other, non-police sources of data concerning heritage crime are available, but they are often patchy in detail. For example, Historic England's annual 'Heritage at Risk Register' notes in a summary whether a heritage site 'has suffered from heritage crime' (Historic England, 2019b, p.xiv) where heritage crime is defined as 'any offence which harms the heritage asset or its setting' (ibid.).

A search of the Register in late 2019 using search terms such as 'crime', 'criminal', 'theft', 'vandalism', 'graffiti' and similar terms elicited 12 'hits' from 484 at risk heritage buildings, locations or sites in the South East of England (approximately 2%). A reasonable assumption would be that this is an under-estimate.

There are further issues with the utility of the database for assessing and monitoring heritage crime. For example, the entry for Murston Old Church, Murston, Sittingbourne notes that the 'building is subject to hertiage crime' (sic) but no further details are provided.

The Bradley et al. (Historic England) report of 2012 (op. cit.) employed five data collection methods (primarily surveys) and found that criminal damage is the most prevalent heritage crime, affecting particularly listed buildings and conservation areas. The November 2011 survey that is described in the 2012 report found that about 19% of all listed buildings were physically affected by crime during the previous year, and for approximately 8% of the listed buildings the impact was substantial (English Heritage, 2012, p.1).

The biggest single crime at the time was metal theft with approximately 7% and 5% of Grade I/II* and Grade II buildings respectively affected with listed churches and other religious buildings being most at risk, with about 38% being damaged by crime (ibid.).

Approximately 15% of listed buildings and 7% of scheduled monuments were subject to criminal damage; 15% of conservation areas experienced crime; antisocial behaviour was the single most common heritage crime concern for scheduled monuments (ibid.).

We compare the Bradley et al. (2012) findings with the outcomes of some of our research in section 9 of this report. In addition, there are other periodic surveys on heritage crime conducted by universities, insurance companies and others. Some of these are specific to particular forms of heritage crime, for example a survey conducted by the security company VPS Group, in 2019 (VPS, 2019).

In 2016 the Department of Security and Crime Science at University College London (UCL) conducted an online survey on the 'theft of cultural property from inside listed or scheduled buildings that are freely open to the public in England, such as churches' (UCL, 2016). However, the results of the survey do not appear to have been published.

The Ecclesiastical Insurance Group appears to collect some unpublished data concerning heritage crime, particularly metal theft from churches. The Group have also supported surveys conducted by organisations such as the Listed Buildings Owners' Club (Ecclesiastical Insurance Group, 2020).

Other statistics concerning heritage crime are also occasionally published although it is not always clear how these have been derived and they also tend to be cited at the aggregate level. For example, the Church of England were cited in Hansard in 2019 as having seen a rise of 25% in metal thefts between 2017 and 2018 (Hansard, 2019).

3.2 Spatial and temporal distribution of heritage crime

Crime may be regarded as an event in space and time that can be analysed by examining the geographical and environmental factors, as well as the wider socio-economic conditions, of its occurrence. The spatial analysis of crime began to receive greater attention from geographers with the implementation of computerised mapping, such as SYMAP (Synagraphic Mapping System, e.g. by Pyle et al., 1974). The further implementation of digital crime databases enabled the greater coordination, analysis and mapping of crime during the 1980s and 1990s.

The development of Geographical Information Systems (GIS), with their ability to store, present and analyse multiple layers of data, improved the capacity for spatio-temporal analysis of crime (e.g. Doran and Lees, 2005) and broadened its application in the field. However, despite the acknowledgement of the geographical factors of crime and its use of GIS, little research has been conducted on the geography of heritage crime. Moreover, these studies have been limited by some of the reporting and recording issues identified earlier in this report.

3.2.1 Crime mapping and heritage crime 'hotspots'

Although there is extensive literature concerning the spatial and temporal dispersal of crime, very little is specific to heritage crime[13].

This may reflect the paucity of reliable and valid data concerning the locations and times at which heritage crimes occur, as well as questions concerning how heritage crime is defined[14]. This is important because research has demonstrated that different crime types of crime can exhibit very different 'patterns'[15] of spatial and temporal distribution.

Crime mapping is a sub-branch of spatial crime analysis, involving the identification of crime 'hotspots'. In this context 'hotspots' are geographic areas with significantly higher rates of recorded crime, antisocial behaviour and disorder than surrounding areas.

[13] Hence one of the reasons for this research project.
[14] We need to know precisely what a phenomenon is before we can measure it accurately.
[15] Where such 'patterns' exist.

Hotspots are familiar to crime analysts and others as a visual representation using GIS (using software such as ArcGIS) linked with crime data. Areas of higher incidence of crime are usually shaded in a stronger colour, such as red, when compared with surrounding areas.

It has long been observed that episodes of recorded crime in an area are not evenly distributed within either space or time. Put simply, some locations appear more prone to crime than others (particularly 'volume crime' such as theft or burglary), either in terms of repeat victimisation or as a general level of crime and disorder.

Similarly, there are particular times of the day or week when crimes are more likely to take place. Furthermore, this clustering in space and time can remain relatively consistent and persistent over a longer period, perhaps even decades.

Although crime hotspots tend to be areas of a few square kilometres, within a hotspot there may be specific locations (for example, the open porchway of a church) which account for particularly high levels of reported crime (sometimes referred to as 'hotpoints' or 'hotdots'). The existence of these hotpoints and the hotspot itself may be partly explained by repeat victimisation[16].

However, crime data collected by the police rarely allows the degree of precision needed to reliably identify such micro hotspots.

Inevitably, there is some debate in the literature concerning how hotspots are identified, such as the unit of measurement used to take the 'temperature' of a supposed hotspot. If we choose to use an absolute scale (e.g. the number of incidents of criminal damage to heritage assets compared to the same period in the previous year) rather than a relative one (e.g. the number of heritage crimes per 1,000 of population) this may affect whether we decide that the data relating to a particular location has reached a threshold, and if that location should be classified as a heritage crime hotspot.

This is particularly important when making comparisons with a certain periodicity such as a week, month or year.

On the technical level, there is often discussion concerning the choice of the kernel density function (a way of measuring the density per unit area).

Although these may appear to be rather arcane and technical discussions, they reflect some fundamental issues concerning how we define and subsequently identify heritage crime hotspots.

As far as the authors are aware, this report constitutes the first study of the crime hotspots within, at or close to heritage locations. The hotspots used in this study

[16] It is interesting to note that repeat victimisation has been used as a 'red flag' to prevent illicit metal detecting at archaeological sites (Grove et al., 2018).

were created using the Kernel Density tool that is part of the Spatial Analyst extension for ArcMap, within the ArcGIS software suite.

An example of a hotspot map produced as part of the research for this report is shown in Figure 1 below. It illustrates the density of criminal damage hotspots within or close to the city of Canterbury's World Heritage Sites.

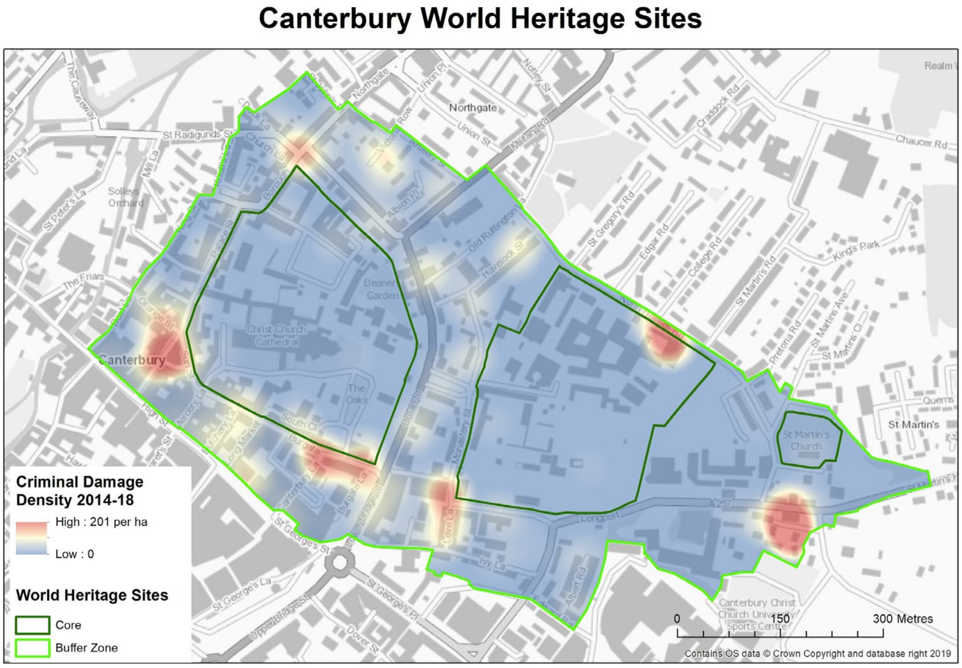

Figure 1 Criminal damage hotspots within or close to Canterbury World Heritage Sites, 2014-2018.

Hotspots were also created for three Heritage Action Zones (HAZs) in Kent and Medway (see section 7). Because of the nature of these Zones, two different search radii were used. In the Ramsgate Zone, and the Swanscombe and Greenhithe Zone, a radius of 100m was used. In the more dispersed Leeds and Hollingbourne Zone a radius of 250m was used. These different distances were necessary to produce recognisable hotspots, so the use of a common radius across all three Zones was not practical.

Strategies designed to tackle crime hotspots must recognise that each area or location has a unique combination of social and environmental factors. There is a danger that geography may be adopted as the single explanatory variable of a hotspot, ignoring the existence of 'lurking' variables such as demography. The aetiology (the exact nature of the causes) that lie behind a particular hotspot may reside, for example, in offenders targeting heritage buildings that happen to spatially cluster in a certain part of town.

Furthermore, identifying a statistical or spatial correlation is quite a separate task to establishing causal links between crime and location. Statistical tests for correlation indicate numerically the strength and direction of a relationship between phenomena, but they do not reveal the degree of causation. For example, the frequency of crime correlates positively with distance from the Equator (Ellis et al., 2009), yet there is no causal link between these two variables. Similarly, spatial correlation tests tend to measure clustering that implies, rather than establishes, causality through spatial coincidence.

More recent research has focussed on the possibility of predicting future crime hotspots, although not specifically for heritage crime. One key criticism of more 'traditional' approaches is that hotspot identification has become an exercise in identifying and mapping past events and provides only a limited guide to the future.

'Predictive hotspotting' on the other hand, derived from disciplines as diverse as behavioural ecology (optimal foraging theory), epidemiology and criminology, would attempt to predict where crimes are likely to occur, and thus, by extension, how best to deploy heritage crime prevention resources or to 'harden' the possible targets.

As part of our research we explored the prospective of using machine learning to develop predictive algorithms. See section 10 in this report.

4 Crime and location data utilised

From the outset it is Important to acknowledge that our research, in the main[17], analysed reported crime at, within or near a building or location with historic value and importance. Clearly, this is not the same as analysing 'heritage crime' per se.

For the purposes of this report we employ the concept of 'Crimes Within, At or Close to Heritage Sites' ('CWACHS')[18]. It is not automatically the case that all, or even most CWACHS are 'genuine' heritage crimes according to the definition adopted by Historic England (see section 2).

An attempt was made to assess the proportion of CWACHS that were targeted heritage crimes using a random sampling technique, both for all heritage sites and for Places of Worship in particular (see sections 6.1 and 8.1).

The Historic England data we collected consisted of publicly available[19] ESRI shapefiles[20], conservation area GIS polygon datasets and GIS data that provided geolocation data for Listed Buildings, Scheduled Monuments, Registered Parks & Gardens, Registered Battlefields, World Heritage Sites, Protected Wreck Sites and 'Heritage At Risk' sites in Kent and Medway.

These data were supplied in two forms:

- Polygons showing precise boundaries for areas such as World Heritage sites; and
- Points showing the centre point of smaller locations such as Listed Buildings. For some analysis, 20m buffers were created around these points to capture crimes that occurred at or were close to these buildings, possibly within their grounds and gardens (see section 5.1).

Some data sets were not used in the analysis. One of these was the 'Protected Wrecks' database, as there were no crimes recorded at these locations.

Although data for the Historic England Conservation Areas appeared to be incomplete, these data were utilised as much as possible. However, for this reason, the results concerning these Conservation Areas should be treated with caution.

Table 2 below indicates the numbers of listed buildings, places of worship, scheduled monuments, conservation areas (where available) and registered parks and gardens used in the analysis[21].

[17] The exception was a search of all crimes in Kent and Medway for specific heritage crime defined under legislation – see section 5.
[18] A term and acronym of our own invention and not used by, for example, Historic England.
[19] After registration.
[20] Environmental Systems Research Institute (ESRI) is a leading manufacturer of GIS software and shapefiles are its principal vector file format.
[21] Note that there is overlap in these categories e.g. some listed buildings can be found within conservation areas.

Heritage location	Total number
Listed buildings	17,949
Places of Worship	1,197
Scheduled Monuments	424
Conservation Areas (where available)	281
Registered Parks and Gardens	62

Table 2 Numbers of listed buildings, places of worship, scheduled monuments, conservation areas (where available) and registered parks and gardens in Kent and Medway used in the analysis.

The anonymised Kent Police recorded crime data were supplied as a set of ten Microsoft Excel spreadsheets, two for each year, with a total of over 1 million entries.

After data cleansing (see below) there were a total of 1,122,180 crimes, which took place between 01/01/2014 and 31/10/2018, i.e. over 1,766 consecutive days. These data incorporated 153 categories of offence.

As much personal data as possible were removed before researchers accessed the data. When necessary for processing, data was transferred between partners using a hardware encrypted[22] USB flash drive and during the course of the research no data was stored on a networked drive. At the end of the project all data were deleted[23].

Care was also taken to ensure that the Information Commissioner's Office guidance concerning 'Crime-mapping and geo spatial crime data: privacy and transparency' (ICO, 2014) was adhered to. This is particularly the case concerning 'indicating crime scenes and levels on crime maps' (ibid.). For this reason, maps showing the detailed distribution of crimes have been not reproduced in this report.

Almost all crimes on the Kent Police database for the period under study were accessed[24]. Each entry contained the following information:

- a unique Crime Reference Number (CRN);
- the time, date and year that the crime was recorded;
- the earliest and latest times and dates that the crime could have occurred;
- Offence Categories and Descriptions (in broad terms); and
- location information, including Ordnance Survey coordinates which enabled each incident to be mapped[25].

Apart from random sampling purposes (see sections 6.1 and 8.1 below) the CRN was not utilised.

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[22] The level of encryption was 256- bit AES.
[23] Using secure file deletion software.
[24] The exception were crimes of a highly sensitive nature e.g. crimes against children, sexual crimes, etc.
[25] However, in order to maintain anonymity, no 'pin-point' maps have been produced for this report.

As in common with much ‘real life’ data, errors are impossible to avoid. In particular, four general sources of error were possible with the Historic England location and Kent Police crime data that were utilised.

Firstly, there may be heritage locations that were not included within Historic England’s database. We judge that these are likely to be relatively few.

Secondly, there may be heritage crimes that went unreported and hence were not recorded in the Kent Police crime database. There are likely to be a significant number of these (see section 2.2).

Thirdly, there are heritage crimes which were reported but erroneously not recorded (i.e. they met Home Office counting rules but were not recorded). These are likely to be relatively few in number, particularly in the latter years of the period under study (see section 2.2).

Finally, there may be heritage crimes on the Kent Police database that are not, in reality crimes. These are likely to be very few in number.

An additional, but more specific, source of error relates to the recording of Ordnance Survey (OS) coordinates when they were entered into the system. It is impossible to state how many errors have been introduced in this way; an obvious example of this error (the corresponding location was in the sea) seemed to have two digits in its Easting coordinate transposed.

One other specific issue that was found with the crime data was an inconsistency in categories and descriptions. This tended to manifest as differences in punctuation, e.g. the inclusion or not of commas, or the use of underscores instead of spaces. It is assumed that the system used will not allow the use of the pound sign (£), as “£5000” appears in multiple forms, e.g. 5000, 5,000, E5000. These inconsistencies had to be taken into account and ‘cleaned’ as necessary before performing our analysis.

For the purposes of the analysis we also collected publicly available data for the Lower Layer Super Output Areas (LSOAs) in Kent and Medway, and extracted geographical data for Places of Worship from the OS OpenData website.

5 Methodology

At the outset of this study, a search by offence headings in the crime database was conducted in an attempt to identify the frequency of heritage-specific crimes, such as the illegal dealing in cultural articles.

The method employed was a complete search of the crime database for key words such as ‘treasure’, ‘ancient’, ‘cultural’, ‘monument’, ‘wreck’ and so on.

5.1 Methodology for spatial analysis

To identify the locations of CWACHS, the methodology for the spatial analysis employed for this project involved superimposing crime locations onto heritage locations and combining relevant layers to create a representative ‘heritage crime’ layer. (In terms of our devised nomenclature, this was termed a ‘CWACHS layer’.)

Where the original Historic England data were supplied as polygons (representing the area footprints of buildings) these were retained, and where the original data were point locations, these were each assigned a 20m buffer (a zone of equal distance from each point of origin) to nominally encompass a building and its immediate surroundings.

Various distances were explored, but 20m was chosen as the most appropriate for this study. (Extending the distance to 50m, for example, increased the number of crimes exponentially, and risked the inclusion of too much additional ‘noise’.)

The size of the 20m buffer therefore represents a compromise between establishing point locations that would obviously lead to close-to-zero heritage crimes being identified, and larger distances, which experimentation showed ‘pulled in’ unrealistic numbers of possible heritage crimes. It also provides an approximation of the ground-floor coverage of buildings, although there is much variation in this.

Figure 2 below shows an example of setting 20m buffers (blue) around listed buildings and a place of worship. Crimes (red) that are located inside the buffers are treated as potential targeted heritage crimes. A preliminary visual analysis of these data, however, does not provide any sense of a spatial correlation between potential heritage crimes and these sites, since the uneven distribution of both variables rarely coincides.

Figure 2 Illustration of the application of 20m buffers around listed buildings and a place of worship

5.2 Classification of crime types

As noted in section 4 of this report, there were a total of 153 offence categories in the Kent Police crime recording system[26]. Clearly, for the purposes of statistical research, the number of categories under consideration needed to be reduced.

Where possible, we retained the original crime classification headings where these represented a reasonably significant volume of offences (i.e. greater than 1% of the total over a period of study). Table 3 shows the crime classification headings used in this research and how they correspond to the Kent Police crime recording system headings and the Home Office Crime Reporting Codes.

Crime classification headings used in this study	**Kent Police NCRS headings**	**HOCR Codes**
Theft -other types	**Theft offences** Attempt theft - other - including by theft ' finding ' Theft of fixture by tenant Theft _ miscellaneous	49
Criminal damage, value £5,000 or less, and malicious damage	**Criminal damage offences** Criminal damage to property valued under £5000	149
Other burglary in building other than dwelling	**Burglary - business and community** Burglary other Burglary - theft Burglary with intent to steal Attempt burglary with intent to steal Burglary - theft / attempt theft with violence Burglary - with intent to commit damage Attempt burglary- with intent to commit damage	30
Theft from a motor vehicle	**Theft from motor vehicle**	45
Burglary residential	**Burglary – residential** **Burglary dwelling** Burglary and theft - no violence Burglary - with intent to steal Burglary - with intent to cause damage	28
Theft from the person	**Theft offences** Theft from the person of another Attempt theft from the person of another	39
Causing intentional harassment, alarm or distress	**Public order offences** Section 4a - use threatening / abusive / insulting words / behaviour to cause harassment / alarm / distress Section 4a - display any writing / sign / visible representation with intent to cause harassment / alarm or distress	125

[26] The system was changed after November 2018 from 'Genesis' (employed during the period under study in this research) to 'Athena'.

Robbery	**Robbery** Robbery Attempt robbery	34
Harassment, alarm or distress	**Public order offences** Use threatening / abusive words / behaviour or disorderly behaviour likely to cause harassment, alarm or distress - section 5 use threatening words / behaviour to cause harassment alarm or distress - section 5 (not used for occurrences after 31/01/2014) Display threatening / abusive writing / sign / visible representation likely to cause harassment / alarm / distress	125
Making off without payment	**Theft offences** Make off without making payment	53
Fear or provocation of violence	**Public order offences** Section 4 - use threatening / abusive / insulting words / behaviour with intent to cause fear of/provoke unlawful violence Section 4 display sign etc intend unlawful violence	125
Theft in a dwelling other than from auto machine/meter	**Theft offences** Theft in dwelling other than auto machine or meter Attempt theft in dwelling other than automatic machine or meter	40
Other	Everything not included in another category in a table.	All other codes

Table 3 Crime type headings mapped to Kent Police headings and HO Codes.

Note that 'Theft -other types' is a very wide-ranging category which includes stealing credit cards, stealing items from lockers at a sports centre, stealing garden items, property stolen from the structure of a non-owner occupied property (e.g. lead from a roof or outside copper piping).

Note also that 'Theft -other types' includes 'removal of articles from places open to the public'.

For the purposes of our analysis, some of the categories were combined in a naturally occurring manner (e.g. the 'public order' offences), particularly where numbers were small. However, were possible we have retained the fine-grained detail available with such a large dataset.

For some analysis, we examined only those entries that contributed at least 1% to the total number of CWACHS. The remainder are included under an 'other' category.

5.3 Methodology for temporal analysis

The methodology adopted in this research for the analysis of temporal data was developed with regard to particular issues associated with the accurate recording of when a crime has occurred. Plotting the times of events proves problematic when the event could have occurred at any time during a 'window'. Many crimes occur at some point during working hours, for example, and in this case the time window on the crime report for an unoccupied listed building might be from 8am (08.00) to 6pm (18.00).

In some cases, the time window was even larger. For example, a crime that occurred when a building was left unoccupied for a period of days or weeks, but which was only discovered on the asset manager's return.

Three approaches to solving this problem were explored:

- Mid-point. This was the easiest to use, the most intuitive, but produced a huge, and unrealistic, spike at midday.
- Random assignment. Placing each crime at a random point within its 'window' has a smoothing effect with larger data sets, but the random effect is more noticeable with smaller samples.
- 'Aoristic' approach. This involves spreading each crime evenly across its 'window', e.g. a crime with a five-hour window contributes 0.2 of a crime to each hour in that window.

Research has shown that aoristic analysis allows for a more accurate estimation of peak offence times[27]. Hence the aoristic approach to assigning time for analysis was adopted for this project.

The analysis was performed using ESRI ArcGIS software, specifically, ArcMap 10.5 with Spatial Analyst and Geostatistical Analyst extensions. The software was used to produce the maps in addition to the initial plotting of the crime data using the Ordnance Survey coordinates supplied. ArcGIS was also used to produce subsets of the main data by extracting crimes based on their type and location. Summary tables of data were then transferred back into Excel for further processing.

5.4 Methods of testing used

Various tests for spatial autocorrelation were used as part of our methodology. Generally, the results of testing for spatial autocorrelation are reproduced in this report where they proved to be relevant to our research aims and objectives.

In particular, the Moran's I test was used to explore the clustering of crime at the Lower Super Output Area (LSOA) level, showing clusters as areas with statistically significant high or low levels of crime.

In addition, statistical tests of difference in proportion or frequency were utilised where appropriate. Methods included the chi-squared test for contingency tables. Software employed included SPSS, Prophet[28] and Excel. The programming language Python 3.6 was used for machine learning, seasonality testing and forecasting.

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[27] One disadvantage of this approach is that, non-mathematically, having 'fractional crimes' can be considered counter-intuitive. However, as Ashby and Bowers (2013) demonstrated, in terms of times of crime it is often preferable over commonly used deterministic methods which they found to be both inaccurate and misleading.

[28] Prophet is a 'procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects' (Facebook, 2020). Prophet is open source software released by Facebook's Core Data Science team.

6 Results of analysis of heritage crime for Kent and Medway

This section of the report presents the results of our frequency, spatial and temporal analyses of heritage crimes (heritage-specific crimes, CWACHS and targeted heritage crimes) in Kent and Medway. The section concludes with a discussion of the results.

6.1 Frequency analysis

As part of our research we conducted an analysis of the numbers of heritage specific offences and the numbers of CWACHS that occurred in Kent and Medway during the period of study.

6.1.1 Frequency analysis of heritage-specific crimes

In section 2.1 above we identified the specific legislation pertaining to heritage crime. At the outset of conducting research for this report we undertook a search of offence headings in the Kent Police crime reporting database in order to identify the frequency of heritage-specific crimes, such as the illegal dealing in cultural articles.

The method employed was a complete search of the crime database for key words such as 'treasure', 'ancient', 'cultural', 'monument', 'wreck', and similar.

Our search of the police database for key words related to heritage-specific crimes gave just three 'hits' from the complete database of 1,122,180 incidents over the period of study (01/01/2014 to 31/10/2018 inclusive). All of these results were for the offence of 'destroy or damage an ancient protected monument'.

This indicates the difficulty of identifying specific heritage crimes within the current police database and highlights the need for a different approach their recording.

6.1.1 Frequency analysis of CWACHS

For the period of study (01/01/2014 to 31/10/2018 inclusive) there were a total of 96,013 recorded CWACHS (crimes within, at or close to a heritage site), spanning 153 crime types, of which 106 recorded at least one crime during the period.

It follows that approximately 9% of all recorded crime in Kent and Medway occurs within, at or close to a heritage site.

The mean[29] number of CWACHS is approximately 19,844 offences per year, or 54 offences per day. However, most of these offences were not likely to have been 'heritage crimes' per se.

In order to gain an estimate of the proportion of CWACHS that recorded targeted heritage crimes, a true random sample of 100 was taken and the crime reports

[29] References to the 'mean' in this report are to the 'arithmetic mean'.

manually inspected[30]. A judgement was then made concerning each crime and how far they met the Historic England definition of a heritage crime (see section 2).

It should be noted that there are a number of possible errors in this undertaking, all of which have a bearing on the reliability of any estimates derived from the sample. Firstly, in any sampling, there will be an unavoidable 'sampling error'. This occurs because we are making observations based on a subset of the population as a whole (in this case CWACHS). Using a true random sample reduces this error as does (to a certain extent) increasing the sample size, but the error cannot be eliminated altogether. The sampling error for our sample is calculated below.

Secondly, crime reports may not convey all the information necessary to arrive at a reliable decision concerning the nature of the 'heritage' dimensions to the crime, or some of the information may be incorrect.

Thirdly, incorrect decisions may be made at the stage of determining the likelihood that a crime report of a CWACHS represents a targeted heritage crime[31].

A true random sample was made by using the unique crime reference numbers (CRN) of the 96,013 CWACHS and employing a random number generator. Each of the 100 CRNs crime reports was then manually inspected to determine how far they represented a targeted heritage crime, using a scale from 'very likely' to 'very unlikely'[32]. The results are given in Table 4 below.

Likelihood of a targeted heritage crime	**Frequency**
Very likely	2
Likely	5
Unlikely	15
Very unlikely	78
Total	**100**

Table 4 Assessment of a likelihood of a targeted heritage crime from the CWACHS.

Combining 'very likely' with 'likely' produces a sample proportion of 0.07 or 7%. However, the population (CWACHS) can only be estimated, given the existence of sampling error. In this case a 95% confidence interval for the population proportion for the sample would be 2% to 12%[33].

Extrapolating this to the population as a whole yields an estimate of the number of recorded targeted heritage crimes in Kent and Medway per year as between about 400 and 2380[34]. This represents a very small proportion of all crime. As noted

[30] This was undertaken by a Kent Police analyst within a secure environment.
[31] As noted earlier we have adopted Grove's (2013) for those 'pure' heritage crimes.
[32] For example, a 'very likely' CWACHS was the damage to shutters of a listed building caused by an apparent attempted theft.
[33] The wide range reflects the relatively small sample size when compared with the population size.
[34] As above.

above, given the limitations of the data, errors endemic to the method employed and the sample size these estimates should be treated with caution.

The numbers of targeted heritage crimes in the sample were too small to justify attempting to determine the rank order of crime types.

6.1.2 Frequency analysis of CWACHS by crime type

Table 5 below lists all CWACHS by crime type that contribute at least 1% to the CWACHS totals, together with an 'other' that constitute the rest. The final column gives the rank order of frequency, highest first.

	2014	2015	2016	2017	2018*	CWACHS Total	CWACHS %	RANK ORDER
Theft-other types	5,551	5,312	5,123	5,421	4,341	25,748	26.8	1
Criminal damage, value £5,000 or less, and malicious damage	3,556	3,376	3,402	4,030	3,344	17,708	18.4	2
Other burglary in building other than dwelling	3,938	3,050	2,823	2,342	1,838	13,991	14.6	3
Theft from a motor vehicle	1,672	1,912	1,967	1,543	1,210	8,304	8.6	4
Burglary residential	2,064	1,501	1,333	1,747	1,270	7,915	8.2	5
Theft from the person	772	866	673	832	642	3,785	3.9	7
Causing intentional harassment, alarm or distress	97	88	218	947	1,584	2,934	3.1	8
Robbery	369	376	352	542	531	2,170	2.3	9
Harassment, alarm or distress	122	76	108	558	1,204	2,068	2.2	10
Making off without payment	340	287	273	223	269	1,392	1.4	11
Fear or provocation of violence	113	97	169	406	474	1,259	1.3	12
Theft in a dwelling other than from auto machine/meter	306	293	159	261	210	1,229	1.3	13
Other	1416	1197	1563	1761	1573	7,510	7.8	6
Totals	20,316	18,431	18,163	20,613	18,490	96,013	100%	N/A

Table 5 All CWACHS by crime type, Kent and Medway, from 01/01/2014 to 31/10/2018.

The 'top three' offence types count for just over half the total number (56.2%); with the remaining 150 distributed between just under one half (43.8%).

Figure 3 below shows the distribution of crime types within the CWACHS total.

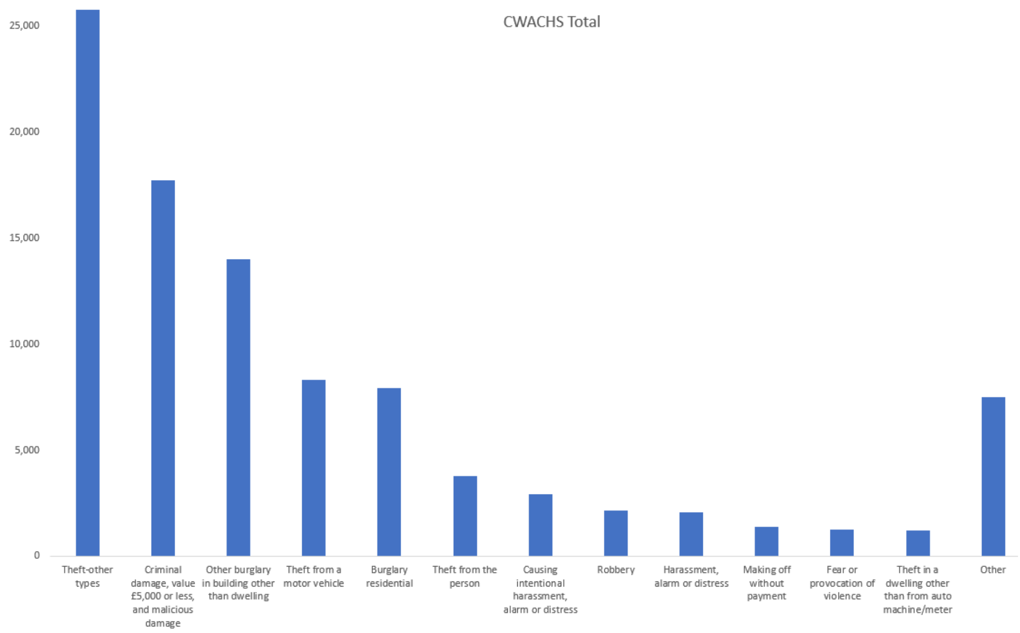

Figure 3 Distribution of crime types within the CWACHS total.

The crime categories in Figure 3 were further grouped together as ‘theft offences’ (combining ‘theft-other types’, ‘theft from a motor vehicle’, ‘theft from the person’, ‘robbery’ and ‘making off without payment’), ‘public order offences’ (combining ‘causing intentional harassment, alarm or distress’ with ‘harassment alarm or distress’ and ‘fear or provocation of violence’), ‘criminal damage’ (’criminal damage, value £5000 or less, and malicious damage’), ‘burglary (dwelling)’ (combining ‘burglary residential’ with ‘theft in a dwelling other than from auto machine/meter’), and ‘burglary (non-dwelling)’ (‘other burglary in building other than a dwelling’).

In terms of overall frequency, the most commonly occurring[35] CWACHS were then ‘theft offences’ (c. 43%), ‘criminal damage’ (c.18%), ‘burglary (non-dwelling)’ (c. 15%), ‘burglary (dwelling)’ (c. 10%) and ‘public order offences’ (c. 6%).

For further comparison, Table 6 was constructed which shows all crime in Kent and Medway for the same time period together with an ‘other’ that constitute the rest. The final column gives the rank order of frequency, highest first.

[35] Excluding ‘other’.

	2014	2015	2016	2017	2018*	Total	Total %	RANK ORDER
Theft-other types	39,676	36,587	37,668	40,724	33,074	187,729	16.7%	2
Criminal damage, value £5,000 or less, and malicious damage	45,922	46,171	47,380	52,857	43,613	235,943	21.0%	1
Other burglary in building other than dwelling	38,135	30,739	30,511	19,388	11,930	130,703	11.6%	5
Theft from a motor vehicle	33,798	30,167	32,706	32,665	27,034	156,370	13.9%	3
Burglary residential	44,829	25,546	21,168	32,760	25,268	149,571	13.3%	4
Theft from the person	4,694	4,552	4,182	4,660	3,288	21,376	1.9%	10
Causing intentional harassment, alarm or distress	839	890	2,116	11,869	20,778	36,492	3.3%	7
Robbery	3,779	3,426	3,617	4,442	4,415	19,679	1.8%	11
Harassment, alarm or distress	823	517	787	4,455	9,836	16,418	1.5%	12
Making off without payment	6,659	6,543	5,486	6,028	4,857	29,573	2.6%	9
Fear or provocation of violence	954	1,048	2,011	4,524	5,497	14,034	1.3%	13
Theft in a dwelling other than from auto machine/meter	7,627	6,252	5,383	5,599	4,968	29,829	2.7%	8
Other	17,400	15,444	17,528	22,389	21,702	94,463	8.4%	6
Totals	**245,135**	**207,882**	**210,543**	**242,360**	**216,260**	**1,122,180**	**100%**	N/A

Table 6 All crime, Kent and Medway, from 01/01/2014 to 31/10/2018.

A comparison of rank orders between CWACHS crime types (Table 5) and all crime ranks (Table 6) using Spearman's correlation coefficient[36] for rank order was calculated and gave the result $r_s = 0.84615$, p (2-tailed) = 0.00027. The correlation between the two rank orders is statistically highly significant. Hence the rank order of frequency of CWACHS in Kent and Medway largely follows that of all crime.

[36] In our case the Spearman rank correlation coefficient is being used to establish whether there is a monotonic relationship between decreases in frequencies between CWACHS and 'all crime'. This is somewhat counter to the usual way that Spearman's is used but has been conducted here as an attempt to compare the two groups.

However, next a Mann-Whitney[37] U test on frequency totals was then conducted to establish whether the two frequency distributions (all crime and CWACHS) have the same shape. The result was a z-score of -4 with a p-value of 0.00006 and hence the result is significant at $p < 0.05$.

It follows that although the rank orders are 'roughly' the same, the distribution of frequencies within crime categories differ significantly. Intuitively, this also appears to be the case when comparing percentages between CWACHS and all crime for the same crime type for a number of the rows.

For this reason, section 6.1.3 that follows compares CWACHS frequencies to 'non heritage' sites.

6.1.3 Frequency analysis of CWACHS compared to all other locations, by crime type

Section 6.1.2 of the report suggested that there were statistical grounds for assuming a difference in the distribution in frequencies betweeen crime types at CWACHS and 'non-CWACHS'[38] locations in Kent and Medway. Accordingly Table 7 was constructed to compare the two.

	'NON-CWACHS' freq. (%)	**CWACHS freq. (%)**
'Theft offences'	373,328 (36.4%)	41,399 (43.1%)
'Criminal damage'	218,235 (21.3%)	17,708 (18.4%)
'Burglary (non-dwelling)'	116,707 (11.4%)	13,996 (14.6%)
'Burglary (dwelling)'	170,256 (16.6%)	9,144 (9.5%)
'Public order offences'[39]	60,683 (5.9%)	6,261 (6.6%)
Other	86,958 (8.5%)	7,505 (7.8%)
Totals	**1,026,167 (100%)**	**96,013 (100%)**

Table 7 Comparison of frequencies CWACHS with NON-CWACHS Kent and Medway, from 01/01/2014 to 31/10/2018.

[37] The Mann-Whitney U test was used as there are two categorical groups and clearly the distributions are 'non-normal. In shape. However, the assumption of independence is not quite true as there is some dependence between CWACHS and 'all crime' as the former is a subset of the latter. Despite this, the relative sizes of each are so different (95 to 91%) that this should not invalidate the assumption of independence required for the test.

[38] By 'non-CWACHS' we mean the geographical areas of Kent that are not heritage locations (e.g. are not Conservation Areas, not within 20m of a Listed Building, etc.). Clearly this is of much bigger size than the total CWACHS areas.

[39] Combines the three categories of 'causing intentional harassment, alarm or distress', 'harassment alarm or distress' and 'fear or provocation of violence').

In order to test for differences in frequencies a Pearson's chi-squared (χ^2) test was performed. This is one of the most commonly used tests for a difference in distribution of categorical variables between two or more independent groups.

However, for the chi-squared test to be valid, a number of assumptions must be upheld. In this case all the assumptions are met[40] other than (possibly) the requirement that there is no relationship between the subjects in each group.

As the BMJ note, 'It is important to emphasise here that χ^2 tests may be carried out for this purpose only on the actual numbers of occurrences, not on percentages, proportions, means of observations, or other derived statistics' (BMJ, 2019). Hence, we have restricted the analysis to frequencies only.

Formally, we are testing a null hypothesis that the proportional frequencies for CWACHS sites are broadly similar when compared with NON-CWACHS sites, against the alternative hypothesis that they are different.

The null hypothesis is either accepted or rejected in favour of the alternative according to a certain chosen level of confidence. For the purposes of this research we have chosen the 5% (0.05) level[41].

When the distributions of the frequencies differ markedly then the chi-squared sum is large; if the differences are small then the chi-squared sum is also small.

In chi-squared testing Table 87 is known as a 'contingency table' which in this case has six rows and two columns[42].

The chi-squared sum for the contingency table is 5027 with a confidence level of p=0.00[43], a highly statistically significant result, which demonstrates that the two groups (in terms of frequencies) are markedly different.

Inspection of residual differences of frequencies suggests[44] that 'theft offences' frequencies are higher for CWACHS, but 'burglary dwelling' is lower. Criminal damage is broadly similar between the two categories.

6.1.4 Frequency analysis of CWACHS by heritage location types

Section 6.1.3 described how testing the data suggested a difference in the distribution of crime types between heritage and non-heritage locations. In this section we explore in more detail any differences within CWACHS according to the type of heritage location.

Note that in what follows, conservation areas include some listed buildings, places of worship and scheduled monuments.

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[40] Our assumptions are that the levels (or categories) of the variables are mutually exclusive, each subject may contribute data to one and only one cell, the groups must be independent, there are two variables, and both are measured as categories, usually at the nominal level and , finally the value of the cell expected values should be five or more in at least 80% of the cells, and no cell should have an expected value of less than one (McHugh, 2013, p.144).

[41] 5% is the normal confidence level used in social science research.

[42] This gives 5 'degrees of freedom' for the test.

[43] This means the value of p is smaller than 0.01 i.e. very unlikely to be down to chance alone.

[44] There is no formal statistical testing available for this.

Table 8 below shows the proportion of different types of heritage location or asset that experienced crime in each of the years (or part year) under study, together with the mean for the whole period.

	Proportion of heritage sites experiencing a crime, within at or in the location					
	2014	2015	2016	2017	2018*	**Mean for all years**
Listed Buildings	18.95%	18.18%	18.40%	19.56%	17.86%	**18.6%**
Places of Worship	27.07%	24.06%	23.64%	28.07%	25.65%	**25.7%**
Scheduled Monuments	11.08%	10.85%	10.38%	11.32%	9.67%	**10.7%**
Conservation Areas	76.87%	78.65%	80.78%	77.58%	78.65%	**78.5%**
Registered Parks and Gardens	54.84%	54.84%	54.84%	54.84%	54.84%	**54.8%**

Table 8 Proportions of heritage locations experiencing a crime (*10 months only).

Our best estimates suggest that approximately one in five listed buildings and one in four places of worship in Kent and Medway experience some form of crime, at or close to them in any given year. About one in 10 scheduled monuments suffer crime at, or it occurs nearby. Just over one half of registered parks or gardens have one or more crimes a year within them. For conservation areas, given they are of relatively large geographical size, the proportion is not unexpectedly much larger at closer to four in five. However. It is important to note that these figures relate to any form of crime and not to heritage-specific or targeted heritage crime in particular.

Table 9 below focusses on how particular crimes are associated with heritage locations (with ‘all crime’ included for comparison).

	All Crime (%)		Listed building (%)	Places of worship (%)	Scheduled monuments (%)	Conservation areas (%)	Registered parks and gardens (%)
Theft-other types	187,729 (16.7%)		17,232 (26.0%)	3,473 (27.0%)	602 (26.9%)	22,943 (25.0%)	765 (29.0%)
Criminal damage, value £5,000 or less, and malicious damage	235,943 (21.0%)		11,828 (17.8%)	2,866 (22.3%)	433 (19.4%)	18,399 (20.1%)	327 (12.4%)
Theft from a motor vehicle	156,370 (13.9%)		5,575 (8.4%)	1,136 (8.8%)	225 (10.1%)	9,128 (10.0%)	275 (10.4%)
Burglary residential	149,571 (13.3%)		7,153 (10.8%)	671 (5.2%)	86 (3.8%)	7,549 (8.2%)	72 (2.7%)
Other burglary in building other than dwelling	130,703 (11.6%)		8,478 (12.8%)	1,857 (14.4%)	332 (14.9%)	10,663 (11.6%)	593 (22.5%)
'Public order offences'[45]	66,944 (6.0%)		4,965 (7.5%)	883 (6.9%)	164 (7.3%)	6,180 (6.7%)	130 (4.9%)
Theft from the person	21,376 (1.9%)		2,620 (3.9%)	326 (2.5%)	83 (3.7%)	3,965 (4.3%)	158 (6.0%)
Robbery	19,679 (1.8%)		1,429 (2.2%)	427 (3.3%)	76 (3.4%)	2,468 (2.7%)	61 (2.3%)
Making off without payment	29,573 (2.6%)		993 (1.5%)	60 (0.5%)	10 (0.4%)	1,442 (1.6%)	19 (0.7%)
Theft in a dwelling other than from auto machine/meter	29,829 (2.7%)		821 (1.2%)	126 (1.0%)	22 (1.0%)	222 (1.0%)	21 (0.8%)
Other	94,463 (8.4%)		5,293 (8.0%)	1,037 (8.1%)	201 (9.0%)	8,681 (9.5%)	214 (8.1%)
Totals	**1,122,180 (100%)**		**66,387 (100%)**	**12,862 (100%)**	**2,234 (100%)**	**91,640 (100%)**	**2,635 (100%)**

Table 9 Comparison of crime within, at or near heritage locations by type of location with all crime, Kent and Medway, from 01/01/2014 to 31/10/2018.

Figure 4 below illustrates the same proportional information as Table 9 but diagrammatically.

[45] Combines the three categories of 'causing intentional harassment, alarm or distress', 'harassment alarm or distress' and 'fear or provocation of violence').

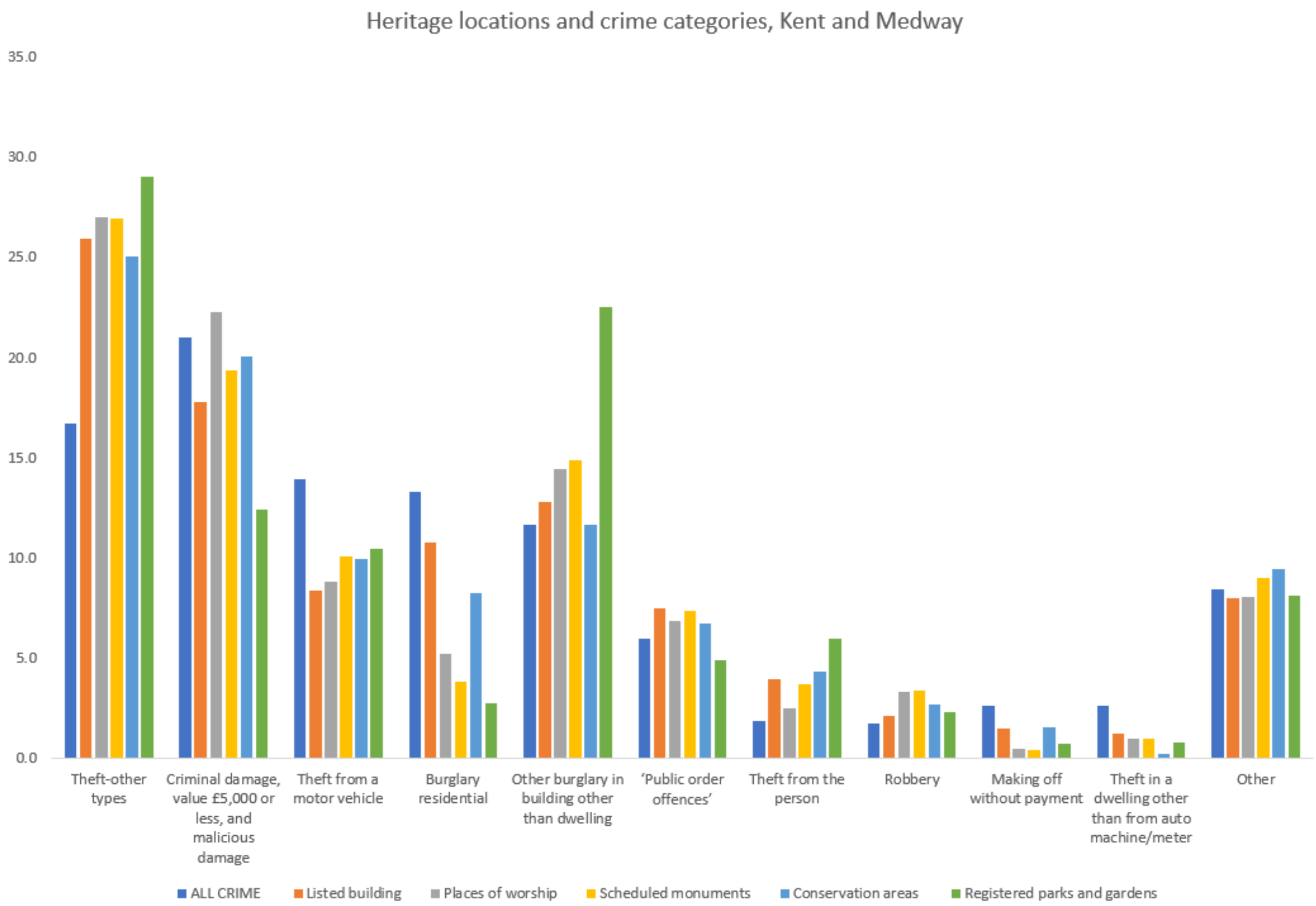

Figure 4 Crime within, at or near heritage locations by type of location, Kent and Medway, from 01/01/2014 to 31/10/2018.

There are clearly significant differences between crime locations in terms of the distribution of proportions of crime types.

Crime categories were then further combined (as earlier) to form Table 10 to provide a 'broader brush' view of differences between different categories of heritage location and crime types.

	All Crime (%)		Listed building (%)	Places of worship (%)	Scheduled monuments (%)	Conservation areas (%)	Registered parks and gardens (%)
'Theft offences'	414,727 (37.0%)		27,849 (41.9%)	5,422 (42.2%)	996 (44.6%)	39,946 (43.6%)	1,278 (48.5%)
'Criminal damage'	235,943 (21.0%)		11,828 (17.8%)	2,866 (22.3%)	433 (19.4%)	18,399 (20.1%)	327 (12.4%)
'Burglary (dwelling)'	149,571 (13.3%)		7,153 (10.8%)	671 (5.2%)	86 (3.8%)	7,549 (8.2%)	72 (2.7%)
'Burglary (non-dwelling)'	160,532 (14.3%)		9,299 (14.0%)	1,983 (15.4%)	354 (15.8%)	10,885 (11.9%)	614 (23.3%)
'Public order offences'[46]	66,944 (6.0%)		4,965 (7.5%)	883 (6.9%)	164 (7.3%)	6,180 (6.7%)	130 (4.9%)
Other	94,463 (8.4%)		5,293 (8.0%)	1,037 (8.1%)	201 (9.0%)	8,681 (9.5%)	214 (8.1%)
Totals	**1,122,180 (100%)**		**66,387 (100%)**	**12,862 (100%)**	**2,234 (100%)**	**91,640 (100%)**	**2,635 (100%)**

Table 10 Comparison of broad crime categories within, at or near heritage locations by type of location with all crime, Kent and Medway, from 01/01/2014 to 31/10/2018.

As is evident from Table 10, the rank of crime categories for Places of Worship, Scheduled Monuments and Conservation Areas is (in decreasing frequency) 'theft offences', 'criminal damage', 'burglary (non-dwelling)', 'public order offences' and 'burglary (dwelling)'.

For listed buildings the order is similar with (in decreasing frequency) 'theft offences', 'criminal damage', 'burglary (non-dwelling)', 'burglary (dwelling)' and 'public order offences'.

Registered Parks and Gardens have a somewhat different rank order with (in decreasing frequency) 'theft offences', burglary (non-dwelling)', 'criminal damage' public order offences' and 'burglary (dwelling)'.

A chi-squared test was carried out for all crime against each heritage location type in turn (other than the conservation areas which occupy large geographical areas). All returned significantly high chi-squared sums. In terms of 'degree of difference'[47] the 'most different' were registered parks and gardens, followed by listed buildings, places of worship and finally scheduled monuments.

Compared to non-heritage locations all of the heritage locations in Kent and Medway have higher 'theft offences' frequencies.

[46] Combines the three categories of 'causing intentional harassment, alarm or distress', 'harassment alarm or distress' and 'fear or provocation of violence'.
[47] The phrase is used in its everyday sense not as a statistical measure. Note also that when comparing 'all crime' with listed buildings, PoWs and scheduled monuments we are not strictly comparing 'like with like'.

Inspection of residual frequencies suggests (not a formal demonstration) that listed buildings experience higher numbers of 'burglaries dwelling' than other locations. This is perhaps unsurprising given that listed buildings may also be often be residential properties[48].

Registered parks and gardens experience higher rates of 'burglary (non-dwellings)' (i.e. from non-domestic properties or buildings such as a shed or garage).

Table 11 below summarises the findings above in less precise and non-technical language. It is, however, an approximation of the more complex 'story' that the data narrates.

CWACHS by heritage location	**Comparison with all crime, Kent and Medway**
Listed buildings	Higher numbers of 'theft offences'
Places of worship Scheduled monuments Conservation areas	Higher numbers of 'theft offences' Lower numbers of 'burglary dwelling'
Registered parks and gardens	Higher numbers of 'theft offences' Higher numbers of 'burglary (non-dwellings)' Lower numbers of 'criminal damage' Lower numbers of 'burglary (dwellings)'

Table 11 Comparison of CWACHS (by heritage location) with all crime in Kent and Medway.

6.2 Spatial analysis

The spatial analysis of CWACHS within Kent and Medway involved in this study included the generation of numerous hotspot maps (see section 5.1 of this report); a selection of which are reproduced in Appendix 1. Also included are hotspot maps for crimes at non-heritage locations for the purposes of comparison.

Figure A1 (in Appendix 1) shows hotspots of all crime in 2017[49] and illustrates the general distribution of crime across the county of Kent and the Medway Unitary Authority area.

The Heritage Locations map, Figure A2 (in Appendix 1) shows the combined layer that was generated from the Listed Buildings, World Heritage Sites, Parks and other

[48] However, 'common sense' results such of this do lend support to the validity of the methodology adopted for the research. See section 5.1 of this report.
[49] The most recent complete year of data available in our research.

heritage locations in Kent and Medway. By definition, CWACHS are those crimes that are located within the red areas shown on the map.

Since many of the heritage locations are found outside towns and cities and they occupy larger areas, a visual comparison of the two maps (Figures 1 and 2) suggests a poor spatial correlation between crime hotspots and heritage locations.

6.2.1 Local Moran's I clustering and heritage locations

To further investigate CWACHS hotspots we employed a well-known[50] indicator (index) of spatial association known as local Moran's I. This tool forms part of the ArcGIS Statistical Analyst Extension and is used to find statistically significant hotspots, coldspots and spatial outliers.

This function requires the data to be stored in polygons with scores for each area, rather than as a series of point locations. Therefore, the crime data were aggregated using Lower Super Output Areas (LSOAs), which are standard small areas used for the analysis of Census data.

The tool then categorises areas into clusters with high or low values, and outliers which have values that are significantly different to their neighbours, whether higher or lower. Many areas, of course, do not fall into any of these categories and in any maps produced are normally left as white in colour.

The use of LSOAs has the benefit that locations are easy to identify, including the three Heritage Action Zones (HAZs)[51] also under study (see section 7 of this report). Visually, one issue with LSOAs is that they differ in size according to their location, e.g. whether urban or rural (when they were created it was intended that the populations would fall within set ranges). Hence, urban LSOAs are much smaller than rural LSOAs, which can give the impression that rural areas with high levels of crime represent much more crime than a few small urban areas with higher levels of crime. This should be taken into account when viewing the maps referenced later in this section.

In addition, as choropleth maps (where areas are shaded according to varying quantities), there is no indication of the relative distribution of crime within each LSOA, since all space within each is treated (and therefore shaded) equally.

In our research, we used the local Moran's I to test[52] to identify four types of clustering within geographical areas of Kent and Medway, as described in Table 12 below.

[50] In addition to crime, Moran's I has been successfully applied in hotspot identification of diseases, mortality rates and pollution (Zhang et al., 2008).
[51] The HAZs are also marked on maps referenced in this section of the report.
[52] In each case a z score and p value were calculated and measured against a level of significance.

Clustering	Explanation
High – High (HH)	High crime locations in the vicinity of other high crime locations
Low-Low (LL)	Low crime locations in the vicinity of other low crime locations
High – Low (HL)	High crime locations in the vicinity of low crime locations
Low – High (LH)	Low crime locations in the vicinity of high crime locations

Table 12 Forms of geographical crime clustering (tested using local Moran's I).

For comparison purposes, Figure A3 (in Appendix 1) shows the four types of clustering for Kent and Medway for the calendar year 2017[53].

Two of most commonly occurring categories of CWACHS in Kent and Medway were 'Theft other types' and 'Criminal damage'. Hence, these are shown in Figure A4 and A5 (Appendix 1).

Intuitively, HH (High-High) and LL (Low-Low) locations require no explanation, since these represent internally consistent clusters[54]. The anomalies are HL (High – Low) and LH (Low – High), which indicate the most significant spatial differences between neighbouring regions. In terms of heritage crime prevention (see section 12.2 of this report), HL locations (areas of high crime in the vicinity of low crime) are of particular interest, as targeting preventative measures here might prove to be more effective in halting the spatial spread of crime. Accordingly, these LSOAs are coloured red in Figures A3, A4 and A5.

Figure A3 reveals a common clustering pattern within urban areas, where there is a high spatial difference of crime clusters between central and peripheral locations (see, for example, Canterbury, Medway and Swanscombe, where central HH areas are surrounded by LH areas). This pattern is repeated for Theft – Other and Criminal Damage (figures A4 and A5). Overlaying Figures A3, A4 and A5 with Figure A2, at an appropriate level (e.g. LSOA) provides an indication of which heritage locations fall within the HL category of interest[55].

For example, there are a number of listed buildings in the Woodnesborough area of East Kent that appear to fall within the HL category for criminal damage.

6.2.2 Urban and rural hotspots

Although most heritage locations are, in terms of area, found in relatively populated areas of Kent and Medway, Figure A2 illustrates that there are very large numbers of listed buildings, scheduled monuments and other sites of heritage value in the less populated, more rural parts of Kent.

It is also the case that, as Kent County Council note, 'People living in urban areas make up 73% of the Kent population but they only occupy 22% of the total land

[53] The most recent complete year under study.
[54] This relates to the so-called 'epidemiology of crime', beyond the scope of this report.
[55] These maps have been omitted on grounds of data protection.

area. The remaining 27% of the population live in rural areas but occupy 78% of the land in Kent'[56] (KKC, 2019).

Hence, as part of the research underpinning this report, we compared how CWACHS were spatially distributed between 'urban' and 'non-urban'[57] areas. Figure A6 (Appendix 1) illustrates the distribution of the geographical locations of the urban and rural areas in Kent and Medway.

Cross-tabulating CWACHS and non-CWACHS crimes with these urban and rural areas produced Table 13 below, reveals the difference in proportions.

	Non-CWACHS		**CWACHS**	
	No.	% Total	No.	% Total
Urban major conurbation	143,991	14.04	5,524	5.75
Urban city and town	668,308	65.15	63,507	66.14
Rural town and fringe	87,569	8.54	8,516	8.87
Rural village	62,845	6.13	8,895	9.26
Rural hamlets and isolated dwellings	63,128	6.15	9,571	9.97

Table 13 Numbers and proportions for Non-CWACHS and CWACHS for urban and rural locations, Kent and Medway, 2014-16.

A chi squared test of the frequencies of Non-CWACHS revealed highly significant differences between the urban and rural locations. Further examination suggests that CWACHS are much higher in rural villages, hamlets and near isolated dwellings than can be attributed to chance. However, they are comparable for rural towns and fringes.

6.3 Temporal analysis of Kent and Medway

In this section of the report we examine how CWACHS vary according to the day of the week, and the month of the year. We also test for underlying temporal trends, in terms of both crime category and heritage location.

As part of the analysis we looked for the existence of any seasonal or cyclical variation.

Seasonal variation refers to a possibility variation in the numbers of CWACHS which occur according to the seasons of the year. As the seasons reoccur every 12 months, seasonal variation is often associated with a 12-month periodicity. So, for example, crime analysts will sometimes compare the incidence of a particular incident this week or month with the same week or month 12 months previously.

However, there is no intrinsic reason why CWACHS should follow a 12-month periodicity. Furthermore, the exact timing of the seasons themselves might vary

[56] As indicated earlier in this report, Medway is predominantly urban in nature.
[57] By 'urban' we mean an 'urban major conurbation' or 'urban city and town'; by 'rural' we mean 'rural town and fringe', 'rural village' or 'rural hamlets and isolated dwellings'. These are combinations used by the Office for National Statistics (ONS, 2013).

from year to year as does the climate during a particular week or month. We used both SPSS and Prophet to test for seasonality in the data.

Cyclical variation refers to regular fluctuations, which are not necessarily seasonal in nature. The periodicity might be over a few days, months or even years. For example, in some countries the number of crimes might demonstrate the same cyclical variation as the economic cycle, over a period of many years.

Despite the possible existence of underlying seasonal or cyclical variation within time series data, *random variation* is also likely to occur. In that sense random variation within our CWACHS data is inevitable and the normal focus of discussion regards how much observed random variation is 'permissible' before the assumption of underlying seasonality should be challenged.

In terms of Kent Police data, the only general recorded crime categories that have hitherto be found to exhibit seasonal variation are bicycle theft and anti-social behaviour and, to a lesser extent public order and violence offences (all four peaking in the summer months)[58] (Doherty, 2018).

6.3.1 CWACHS variation by month of year and day of week

The variation of CWACHS according to the time of year and day of the week is of obvious interest in terms of crime prevention (see section 11.2).

For comparison purposes, 'all crime data' were tested first tested for seasonality. There was only weak evidence of seasonality, which was the peaking of all crime frequency in mid-June and early January with troughs in late August and mid-December. There was no apparent cyclical variation.

Identification of any underlying trends was also undertaken, using the Prophet forecasting procedure and the result is shown in Figure 5.

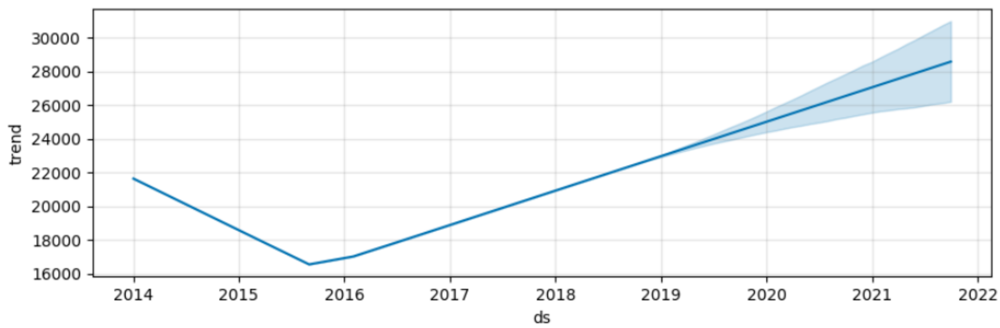

Figure 5 Representation of underlying trend (and forecast) of 'all crime' in Kent and Medway.

It appears that 'all crime' in Kent and Medway began to rise in late Summer/early Autumn of 2015 after falling in the years previously.

Using the Prophet model, an underlying trend line[59] was fitted to the data as shown in Figure 6 (together with the monthly totals).

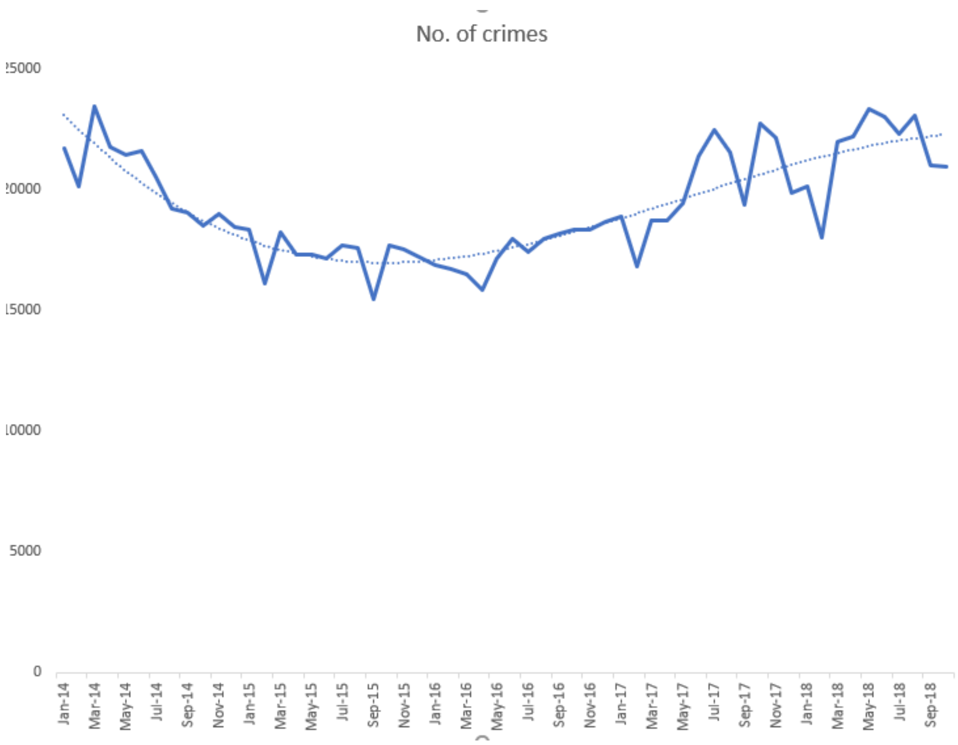

Figure 6 'All crime' in Kent and Medway, together with trend line, from 01/01/2014 to 31/10/2018.

Next, a similar process was undertaken for the CWACHS temporal data for Kent and Medway. Again, there was only weak evidence for the existence of seasonal variation, with 'public order' offences tending to be lower in the winter, theft offences higher in the summer.

The CWACHS data was tested for the underlying trend and the result was used to create a trend line for the CWACHS data which is shown in Figure 7.

59 A polynomial of degree two.

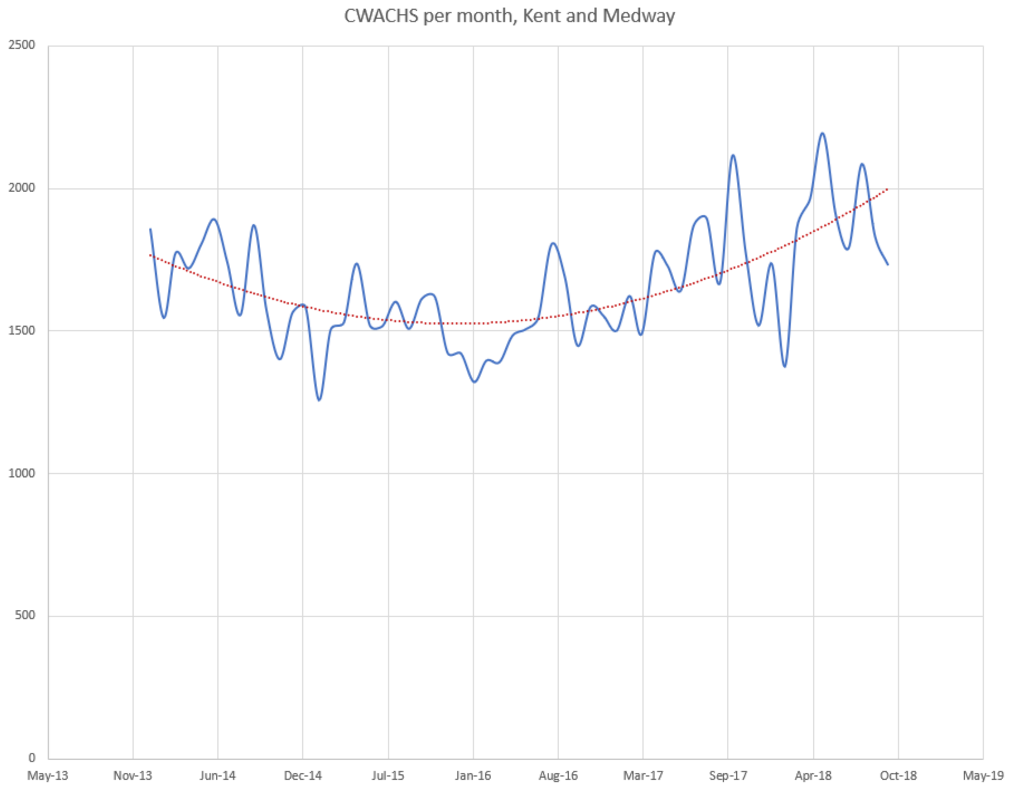

Figure 7 CWACHS monthly totals together with underlying trend line, Kent and Medway, from 01/01/2014 to 31/10/2018.

As with 'all crime', CWACHS were in decline until about the late Summer/early Autumn of 2015 and then began to rise.

Hence both all crime and CWACHS numbers have been growing in frequency since about late Summer/early Autumn of 2015. To test whether the rates of growth were similar the ratio of CWACHS to all crime was calculated on a monthly basis and results (together with an underlying trend line) are shown in Figure 8.

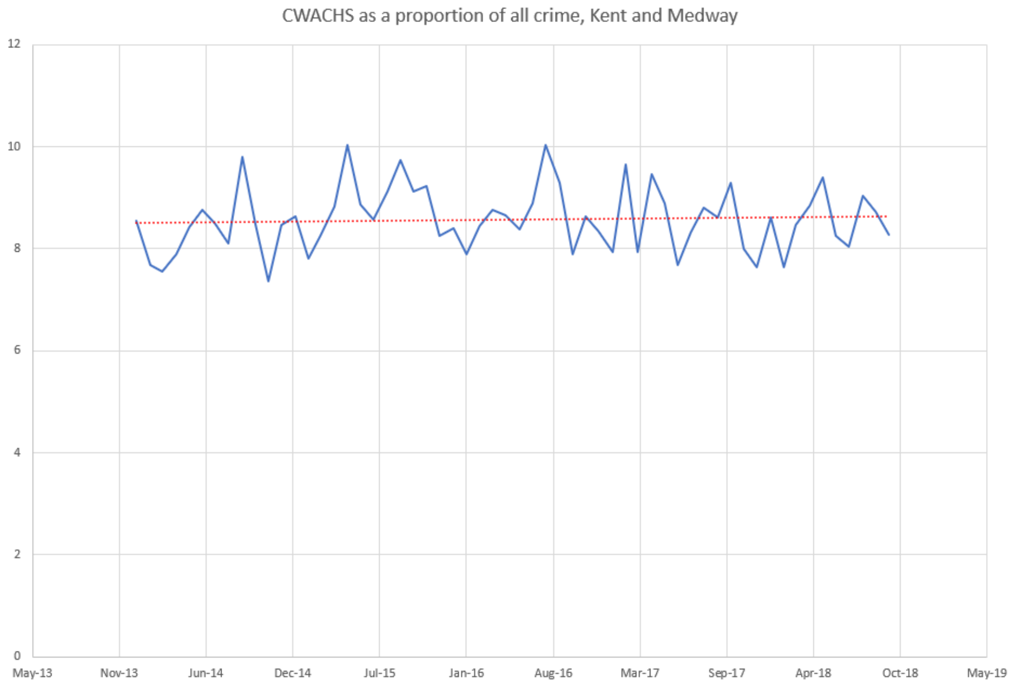

Figure 8 CWACHS as a proportion of all crime, Kent and Medway, monthly totals, from 01/01/2014 to 31/10/2018.

As is evident from Figure 8, the proportion of all crime attributable to CWACHS remained relatively stable in the period 01/01/2014 to 31/10/2018. Hence although the numbers of CWACHS are increasing they are doing so at about the same rate as all crime.

A further investigation in the temporal trends in CWACHS was then conducted in terms of crime types, using the broader categories of ‘theft offences’, ‘criminal damage’, ‘burglary (dwelling)’, ‘burglary (non-dwelling)’, ‘public order offences’ and ‘other’. The result is shown as a stacked area plot in Figure 9.

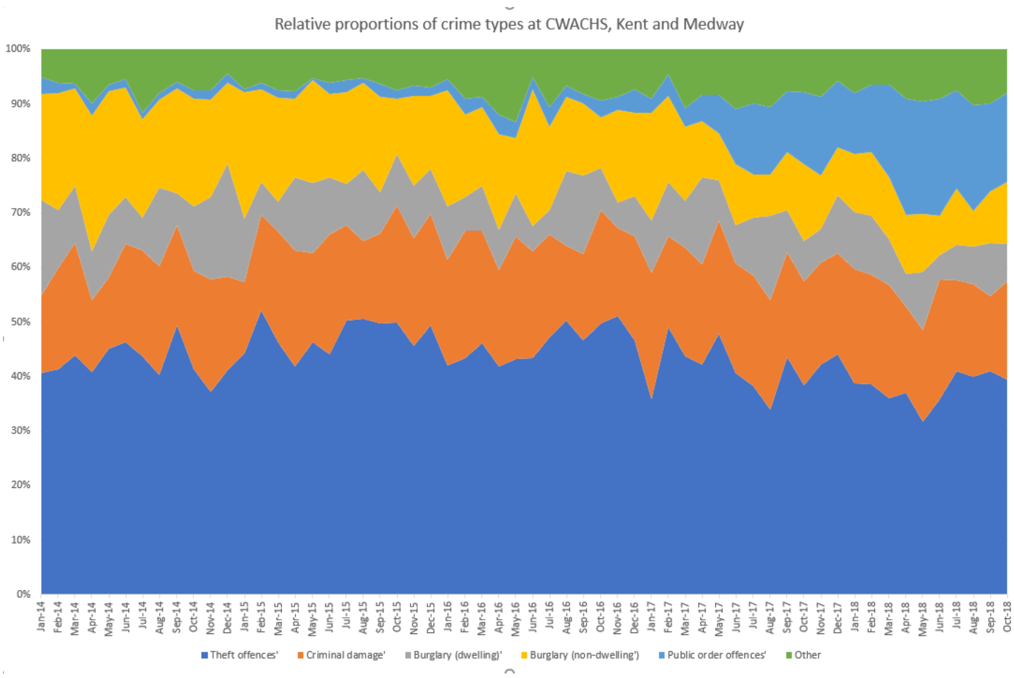

Figure 9 Stacked area plot showing relative proportions of generalised crime categories and CWACHS, Kent and Medway, from 01/01/2014 to 31/10/2018.

As can be seen, the most notable feature of Figure 9 is the number of 'public order offences' at CWACHS growing as a proportion of the total.

6.3.1.3 CWACHS by time of day

Some crimes might vary not only in parallel with the seasons of the year but also according to the time of day.

In the first instance we examined all crime for variation according to time of day[60] for each of the three years and 10 months under study. The result is shown in Figure 10.

[60] We used the aoristic method to determine time of crime (see section 5.3).

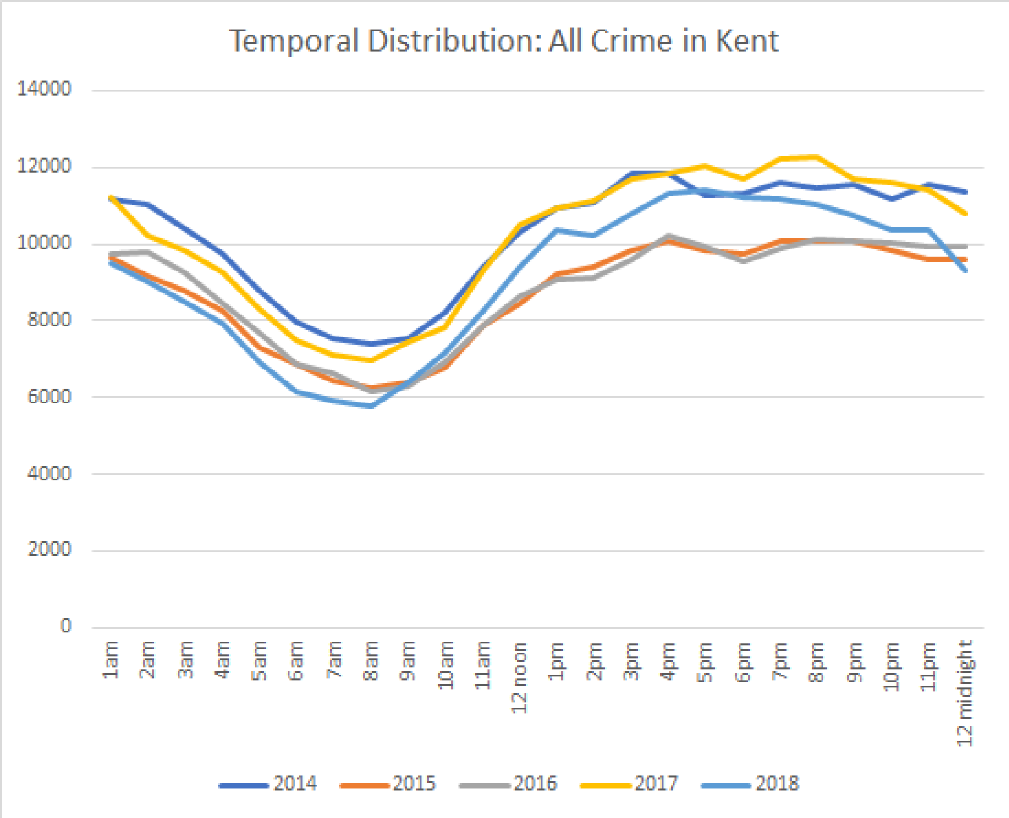

Figure 10 Time of day at which CWACHS occurred, Kent and Medway, from 01/01/2014 to 31/10/2018.

As can be seen from Figure 10, the time of day at which crimes occur in Kent and Medway remained consistent for each year (or part of year) analysed as part of this research. Cyclical variation according to time of day appears evident: troughing at around 8am rising steeply soon after, plateauing after about 3pm until about midnight, and then declining steeply.

In comparison, Figure 11 below shows the times of day at which CWACHS occur in Kent and Medway.

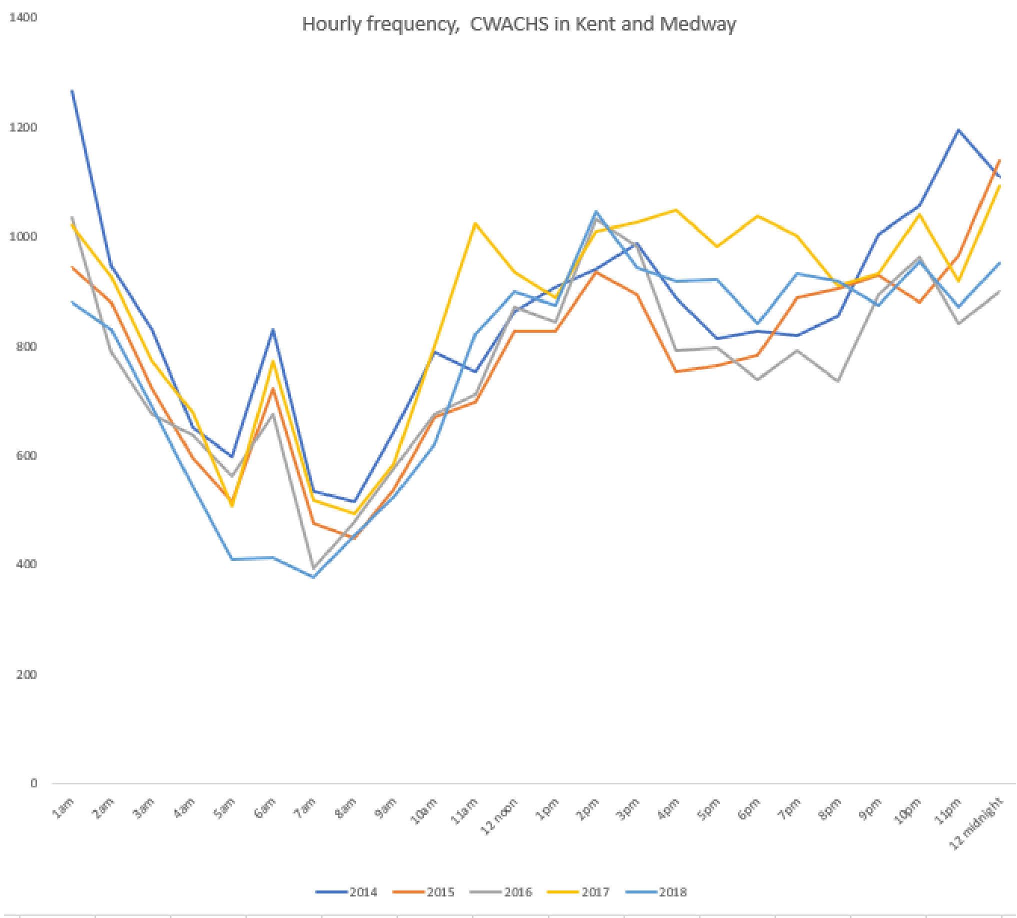

Figure 11 Times at which CWACHS occur for each year under study, Kent and Medway, from 01/01/2014 to 31/10/2018.

There is more variability in time of day for CWACHS for each of the four years studied, but this is possibility attributable to it being a smaller dataset rather than any other effect[61].

The general cyclical variation according to time of day of CWACHS appears to approximately follow the same as that of all crime: a minimum at around 7am, rising relatively quickly until about 2pm, constant thereafter until about midnight and then declining steeply. However, one noticeable difference between CWACHS and other crimes (particularly in recent years) is a marked 'spike' in offending at around 6am.

6.4 Discussion of results

In this subsection, we discuss the main findings of our frequency, spatial and temporal analysis above and examine how these relate heritage-specific, targeted heritage crime and CWACHS.

It is currently not possible to report with any reliability the frequency of heritage-specific crimes in Kent and Medway between 2014 and 2018. We note the difficulty

[61] Possibly as a result in 'smoothing out' random noise, although this is speculative.

of identifying specific heritage crimes within the current police database, which suggests the need for a different approach their recording.

The number of heritage-specific crimes we did manage to identify is clearly an underestimate but the reasons for this are unclear. The most likely explanations are that either the NCRS does not lend itself easily to identification of heritage-specific offences and/or that recording methods are not suitable for these forms of crime[62].

This is not a problem unique to the Kent Police crime database. For example, a Freedom of Information request to West Midlands Police in 2018 asking for the numbers of heritage-specific crimes[63] in the three years 2015, 2016 and 2017 elicited the response of one case of metal (lead) theft (West Midlands Police, 2018).

We can be more confident in our estimate of the frequency of crimes within, at or close to heritage sites (CWACHS). For the period of study (01/01/2014 to 31/10/2018 inclusive) there were a total of 96,013 recorded CWACHS (crimes within, at or close to a heritage site), spanning 153 crime types, of which 106 recorded at least one crime during the period.

Approximately 9% of all recorded crime in Kent and Medway occurs within, at or close to a heritage site.

The most commonly occurring CWACHS are ‘theft offences’ (c. 43%), ‘criminal damage’ (c.18%), ‘burglary (non-dwelling)’ (c. 15%), ‘burglary (dwelling)’ (c. 10%) and ‘public order offences’ (c. 6%). Compared to non-heritage locations, heritage locations in Kent and Medway have higher numbers of ‘theft offences’[64].

Approximately 7% of CWACHS are targeted heritage crimes, but the true value may be between 2% and 12%.

In any given year approximately 19% of Listed Buildings, 26% of Places of Worship, 11% of Scheduled Monuments, 78% of Conservation Areas and 55% of Registered Parks and Gardens in Kent and Medway experience a recorded crime.

Crimes at Places of Worship, Scheduled Monuments and Conservation Areas follow the same rank order of (in decreasing frequency) ‘theft offences’, ‘criminal damage’, ‘burglary (non-dwelling)’, ‘public order offences’ and ‘burglary (dwelling).

Registered Parks and Gardens have a somewhat different rank order with (in decreasing frequency) ‘theft offences’, burglary (non-dwelling)’, ‘criminal damage’ public order offences’ and ‘burglary (dwelling)’.

Numbers of CWACHS are much higher in rural villages, hamlets and near isolated dwellings in Kent and Medway than can be attributed to chance. However, they are comparable for rural towns and fringes.

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[62] We understand that a separate report is being prepared for Historic England on this issue.
[63] The criteria were ‘Nighthawking / night hawking / looting / illicit metal detecting / illegal metal detecting / going equipped with a metal detector / theft from archaeological site / theft from heritage asset / theft from ground’.
[64] Lending some statistical support to a 2019 Listed Property Owners Club Survey which listed theft as being the biggest problem (Ecclesiastical, 2020).

The frequency of CWACHS in Kent and Medway were in decline until about the late Summer/early Autumn of 2015 and then began to rise. However, the rate of increase in numbers of CWACHS are increasing is comparable to that of ‘all crime’ in Kent and Medway.

The number of ‘public order offences’ at CWACHS growing as a proportion of the total, and this in part explains some of the overall increase since 2015.

The general cyclical variation according to time of day of CWACHS appears to approximately follow the same as that of all crime: a minimum at around 7am, rising relatively quickly until about 2pm, constant thereafter until about midnight and then declining steeply. However, one noticeable difference between CWACHS and other crimes (particularly in recent years) is a marked ‘spike’ in offending at around 6am.

Regarding the spatial analysis of CWACHS, we identified significant areas (defined by LSOA units) by applying local Moran’s I. Strong clusters of crime, as indicated by HH (High – High; locations which are areas of high levels of crime in the vicinity of other areas of high levels of crime), tend to exist within urban areas. Similarly, strong clusters of low crime, as indicated by LL (Low – Low; locations which are areas of low levels of crime in the vicinity of other low areas of crime), tend to exist within rural areas.

This test revealed the most significant spatial differences between neighbouring regions (e.g. areas of high crime in the vicinity of low crime) occur on the fringes of urban areas. Hence, a strategy to target preventative measures in these areas might prove to be more effective in halting the spatial spread of crime.

A further examination of the data suggests that CWACHS are much higher in rural villages, hamlets and near-isolated dwellings than can be attributed to chance. However, a comparison of the local Moran’s I results with CWACHS suggests that remote heritage locations are no more vulnerable than urban locations, but that heritage locations located within the periphery of urban areas may be most vulnerable to heritage crime.

Of course, the nature of buildings themselves may influence these results. For example, it is possible that listed buildings are located in areas that increase their vulnerability, but the presence of more outbuildings gives better protection of the building itself. More research is needed to explore this variable in more detail.

It is also possible that greater numbers of CWACHS in rural areas go unreported and the prevention of heritage crime in these areas is more difficult due to lack of surveillance and intervention.

The geographical scale of these analyses allows a broader picture of CWACHS in Kent and Medway to emerge, although, as already mentioned, the mapping of crime using unit-area quantities (in this case, choropleth maps using LSOAs), can give a false impression of distribution. The next section examines three areas at a finer level of detail and allow spatial distribution of crime within urban areas to be appreciated.

7 Heritage crime analysis for Leeds & Hollingbourne, Ramsgate, Swanscombe & Greenhithe HAZs

In this section of the report, we analyse the frequency, spatial and temporal distribution of crime in three 'Heritage Action Zones' (HAZs)[65] in Kent and Medway: those of Leeds & Hollingbourne, Ramsgate and Swanscombe & Greenhithe. The geographical locations of the three zones are shown in Figure A7 (in Appendix 1).

We undertook a separate analysis of the HAZs for two main reasons: to assess the impact, if any, of the HAZ initiative on the frequency of CWACHS in these areas, and, secondly, to undertake a more localised analysis of CWACHS that is not possible with the county-level approach using LSOA units.

The three zones are very different in 'character'. As shown in Table 14 below, they differ greatly in size and population.

	Leeds and Hollingbourne	**Ramsgate**	**Swanscombe and Greenhithe**
Population (2011)	4,839	16,262	14,128
Area (hectares)	7,773	239	863
Population Density	0.623	68.042	16.371
Listed Buildings	246	343	30
Places of Worship	13	14	5
Scheduled Monuments	3	0	2
Heritage at Risk	4	1	1
Parks and Gardens	1	1	0

Table 14 A comparison between the three HAZs.

Leeds and Hollingbourne is a sprawling rural area in the heart of Kent, which includes Leeds Castle. It is the largest and most affluent of the three Zones, with an average Index of Multiple Deprivation (IMD) Rank of 17,530 (lower ranks indicate increasing deprivation)[66]. In the Income indicator for the IMD, the scores for this area range from 0.065 to 0.08, with an average of 0.0725 (higher scores indicate lower average incomes).

Swanscombe and Greenhithe is a rapidly developing area, which includes the Ebbsfleet International railway station, and is adjacent to the Bluewater Shopping Centre. Its average IMD Rank is 11,440, placing it in the middle of the three zones. For the Income indicator for the IMD, the scores for this area range from 0.044 to 0.261, with an average of 0.13. This score places the area in the middle of the three HAZs for average incomes.

Ramsgate is the smallest of the three zones, but has the largest population and also the most Listed Buildings and Places of Worship. It is the most deprived of the three Zones, with an average IMD Rank of 7,122. In the Income indicator for the IMD, the

[65] 'Heritage Action Zones' are an initiative of Historic England who work together with local authorities and other partners and includes grants to restore neglected historic buildings and make improvements to conservation areas (Historic England, 2019c).

[66] All LSOAs in England are ranked 1 to 32,844. It is therefore possible to calculate an average of the LSOAs within the HAZ.

scores for this area range from 0.14 to 0.331, with an average of 0.225 (High Scores indicate lower average incomes).

7.1 Frequency analysis of HAZs

Table 15 below summarises all crime within the three Zones, with raw numbers and percentages for each Zone for those categories which contribute at least 1% of crime for at least one of the Zones. They are listed in descending order of the combined total.

Note that some crime categories have been combined ('public order offences') whereas others have been separated out where they appear to show differences between HAZs.

	Leeds and Hollingbourne	Ramsgate	Swanscombe and Greenhithe
Criminal damage, value £5,000 or less, and malicious damage	644 (13.4%)	4,798 (25.8%)	2,635 (24.12%)
Theft-other types	861 (17.9%)	3,469 (18.7%)	1,241 (11.4%)
Theft from a motor vehicle	751 (15.6%)	1,946 (10.5%)	1,737 (15.9%)
Other burglary in building other than dwelling	870 (18.1%)	950 (5.1%)	1,529 (14.0%)
Other burglary in a dwelling	468 (9.7%)	1,370 (7.4%)	501 (4.6%)
Burglary residential	267 (5.6%)	673 (3.6%)	426 (3.9%)
Theft in a dwelling other than from auto machine/meter	40 (0.8%)	920 (5.0%)	282 (2.6%)
Causing intentional harassment, alarm or distress	79 (1.6%)	607 (3.3%)	414 (3.8%)
Making off without payment	334 (6.9%)	128 (0.7%)	372 (3.4%)
Robbery	12 (0.3%)	645 (3.5%)	169 (1.6%)
Harassment, alarm or distress	39 (0.8%)	422 (2.3%)	146 (1.3%)
Theft from the person	12 (0.3%)	522 (2.8%)	31 (0.3%)
Burglary business and community	121 (2.5%)	236 (1.3%)	155 (1.4%)
Fear or provocation of violence	17 (0.35%)	278 (1.5%)	139 (1.3%)
Threats to commit criminal damage	23 (0.5%)	252 (1.4%)	142 (1.3%)
Attempted burglary in a building other than a dwelling	66 (1.4%)	68 (0.4%)	253 (2.3%)
Attempted burglary in a dwelling	20 (0.4%)	140 (0.8%)	127 (1.2%)

Other categories (less than 1% of crime in study area)	179 (3.7%)	1,141 (6.2%)	607 (5.6%)
Total	**4803 (100%)**	**18,565 (100%)**	**10,906 (100%)**

Table 15 Numbers and proportions of crimes at the three HAZs, from 01/01/2014 to 31/10/2018.

A chi-squared test on frequencies yielded high chi-squared sums which indicated that, in terms of crime types, the three HAZs differ markedly from one another (as is also evident, intuitively at least, with the proportions).

Figure 12 below illustrates the distribution of crime categories for the three HAZs (showing those crime types which account for at least 5% of crimes in one or more of the Zones).

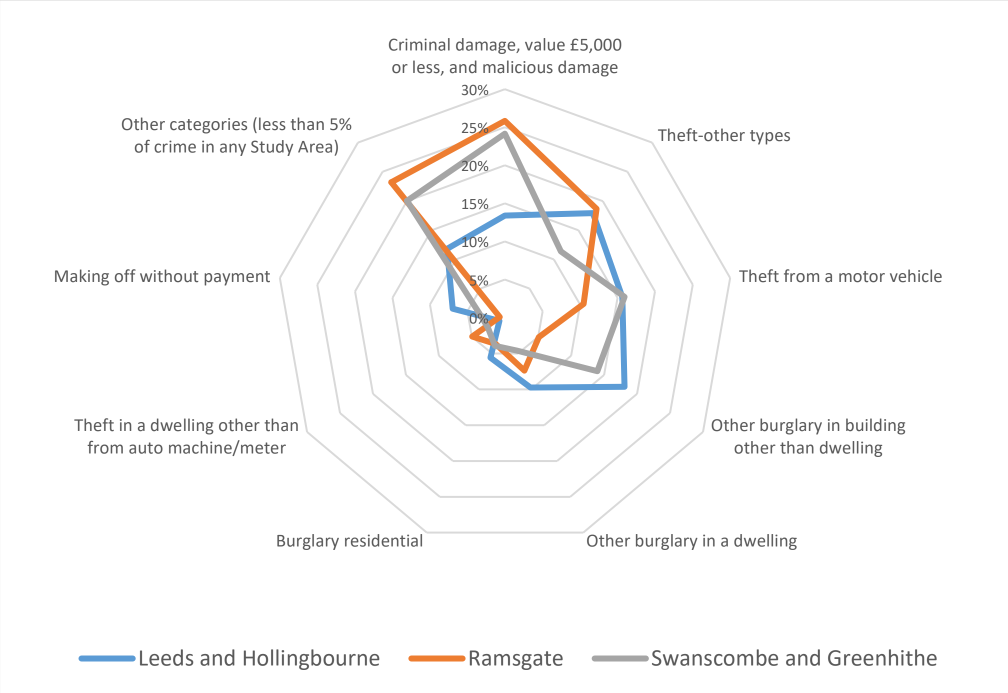

Figure 12 Radar plot of crime types for each HAZ involving crime types that account for at least 5% of crimes in one or more of each Zone.

As Figure 12 demonstrates, the three zones differ in overall crime distribution although there is greater similarity between Ramsgate and Swanscombe and Greenhithe than with Leeds and Hollingbourne (the latter being more of an ‘outlier’, with fewer ‘criminal damage’ and ‘other’ crimes).

The above analysis is for all crime. Table 14 below summarises CWACHS for the three HAZs in particular, after grouping some offences together.

	Leeds and Hollingbourne	Ramsgate	Swanscombe and Greenhithe
Criminal damage, value £5,000 or less, and malicious damage	90 (12.5%)	1229 (25.3%)	60 (36.8%)
Theft-other types	139 (19.3%)	1107 (22.8%)	38 (23.3%)
Other burglary in building other than dwelling	235 (32.6%)	261 (5.4%)	2 (1.2%)
Theft from a motor vehicle	64 (8.9%)	413 (8.5%)	19 (11.7%)
Burglary residential	69 (9.6%)	523 (10.8%)	6 (3.7%)
'Public order offences'	22 (3.1%)	398 (8.2%)	23 (14.2%)
Robbery	0 (0.0%)	166 (3.4%)	7 (4.3%)
Theft from the person	5 (0.7%)	167 (3.4%)	0 (0.0%)
Theft in a dwelling other than from auto machine/meter	0 (0.0%)	157 (3.2%)	0 (0.0%)
Burglary business and community	40 (5.6%)	112 (2.3%)	0 (0.0%)
Attempted burglary in a dwelling	12 (1.7%)	44 (0.9%)	0 (0.0%)
Making off without payment	7 (1.0%)	38 (0.8%)	6 (3.7%)
Attempted burglary in a building other than a dwelling	11 (1.5%)	15 (0.3%)	0 (0.0%)
Other categories (less than 1% of crime in any of the three HAZs)	26 (3.7%)	221 (4.8%)	2 (1.2%)
Total	**720 (100%)**	**4,851 (100%)**	**163 (100%)**

Table 16 Numbers and proportions of CWACHS for three HAZs, from 01/01/2014 to 1/10/2018.

A chi-squared test performed on a contingency derived from Table 14 above demonstrated a highly significant difference in proportions between the three HAZs.

Figure 13 below illustrates how proportions of CWACHS crime categories are markedly different amongst the three HAZs. Again, Leeds and Hollingbourne is an outlier, with a relatively high proportion in the 'Other burglary' crime category.

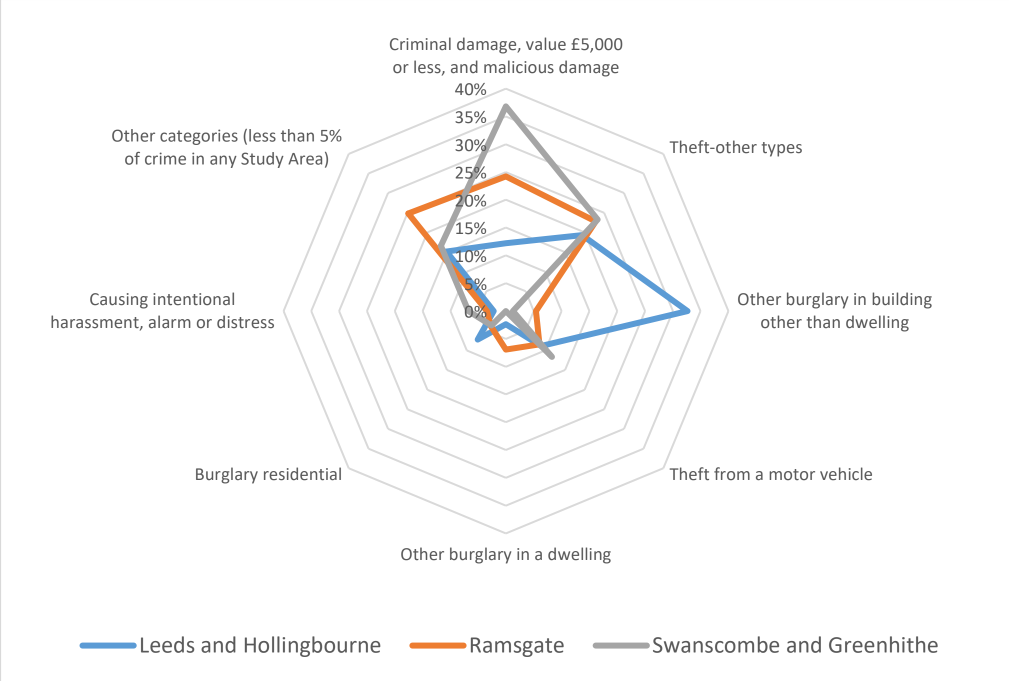

Figure 13 Radar plot of CWACHS categories for each HAZ.

A comparison of the above radar plots illustrates that in general terms, just as with all crime, the distribution of proportions for CWACHS crime categories is similar between Ramsgate and Swanscombe and Greenhithe, and these HAZs are very different to Leeds and Hollingbourne.

In terms of specific categories of CWACHS, Swanscombe and Greenhithe exhibits relatively high levels of criminal damage whereas Leeds and Hollingbourne has high levels of 'non-dwelling burglary'.

7.2 Spatial analysis of HAZs

In this subsection of the report, we present the results of our spatial analysis of CWACHS within the three HAZs.

Firstly, Figure A7 (Appendix 1) indicates the geographical locations of the HAZs in Kent, as well as their relative sizes and urban/rural characteristics. For example, the Leeds and Hollingbourne HAZ covers the largest area and is located in the centre of the county in a predominantly rural environment. This lies in contrast to the other HAZs, which are each located at the geographical extremes of the county and are much smaller and more densely populated (see Table 15).

In addition, although Ramsgate and Swanscombe and Greenhithe are both located in urban areas that are bounded to the east and north respectively by physical barriers (the English Channel and the River Thames), they are different in terms of their internal accessibility. Ramsgate comprises a well-connected street network that has grown up around the historic harbour, while Swanscombe and Greenhithe covers a highly dissected landscape where accessibility is limited to specific road corridors that surround the many quarries that characterise the area. Moreover, in contrast to Ramsgate, this HAZ is subject to ongoing rapid building work as a major transport hub and commuter settlement following the opening of Ebbsfleet

International Station in 2007 and the development of the nearby Garden City Healthy New Town.

The selection of maps in this section present the results of the spatial analysis in turn for each HAZ. These illustrate the spatial distribution of all crime in each HAZ, followed by hotspot maps for specific crime categories.

7.2.1 Leeds and Hollingbourne Maps

Figure 15 provides a hotspot map showing the spatial distribution of all crimes in the Leeds and Hollingbourne HAZ.

In common with all hotspot maps, this indicates the relative density of events (crimes), by assigning colour 'temperature' according to their proximity from each other. The method allows a visual impression of spatial distribution and density, since values between events are interpolated to give a continuous surface.

In general, the incidents of crime each have a close proximity to a road, hence access is an important factor. The map shows that there are concentrated pockets of crime towards the south east of the HAZ, in particular, to the north and south of Leeds Castle and to the north of the HAZ surrounding Yelsted and Stockbury.

The concentrated areas (in red) to the north of Leeds Castle include Hollingbourne station, the public car park of Leeds Castle, and the Maidstone service station for the M20. Leeds Castle itself is highlighted as a crime hotspot, although the major concentration lies to the south, at Kingswood.

Investigating the spatial coincidence of heritage sites (in green) with the hotspots, there is a weak visual correlation and so separate layers of data were analysed.

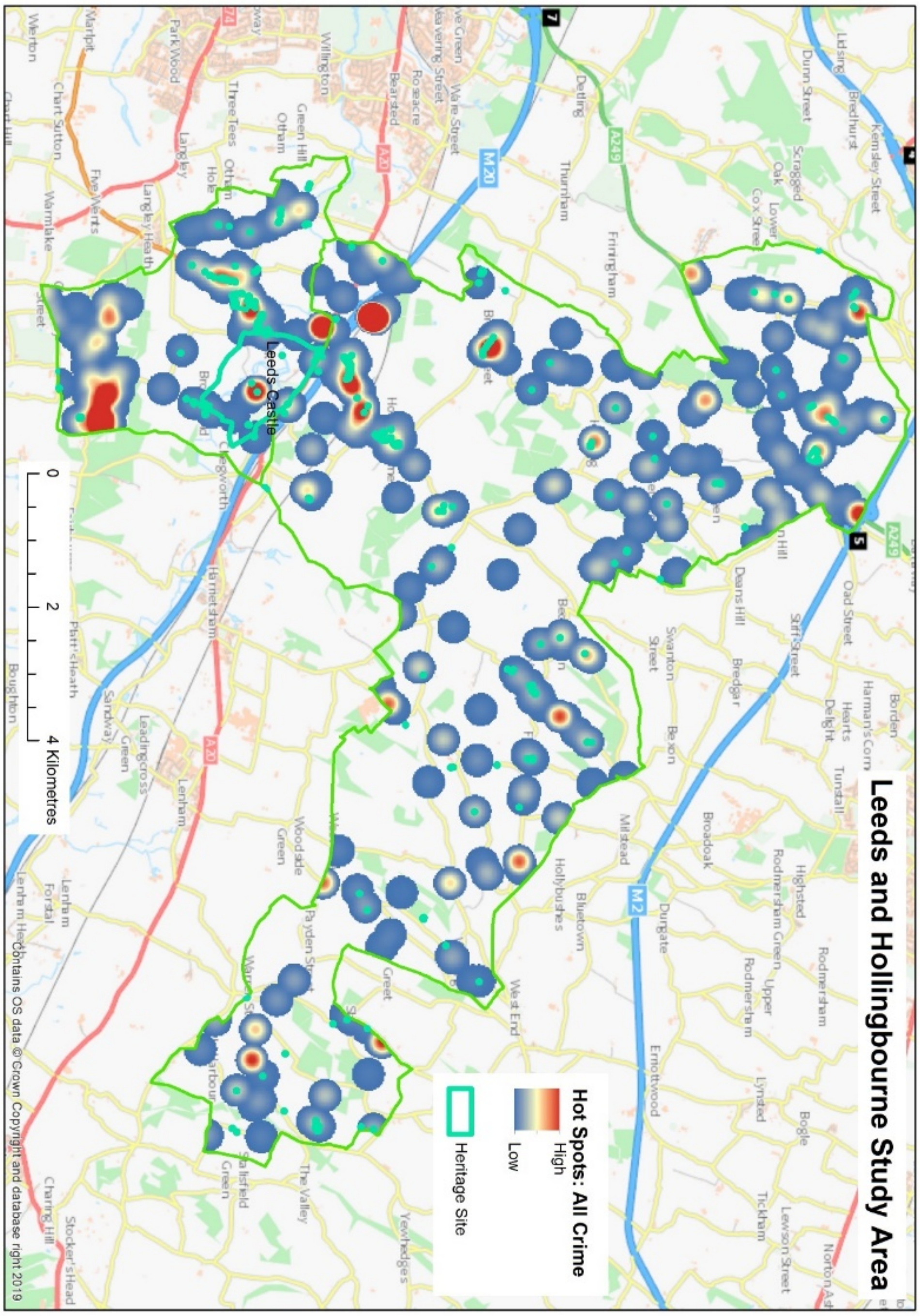

Figure 15 ‘All crime’ in the Leeds and Hollingbourne HAZ.

The next map (Figure 16) highlights the places of worship (PoWs) in the HAZ that coincide with crime hotspots. There are only three of these, namely the churches of X, Y, and Z[67] – all small, rural parish churches situated in villages.

Figure 17 is a hotspot map of the same HAZ showing crimes falling into the category of 'Theft – other'.

The distribution pattern of these crimes and their density largely reflects that of Figure 15, which indicates the distribution of all crime. However, while there are concentrations in similar locations, there appears to be a greater coincidence of crime hotspots within or near to heritage sites with this category of crime. This may suggest that the designation of this area as a HAZ is having limited success.

Moreover, it is easier to distinguish a distinctive linear pattern of hotspots stretching south west along the B2163 from Hollingbourne and to identify specific concentrations of crime surrounding the village of Kingswood to the south of the HAZ.

[67] Names removed for data protection purposes.

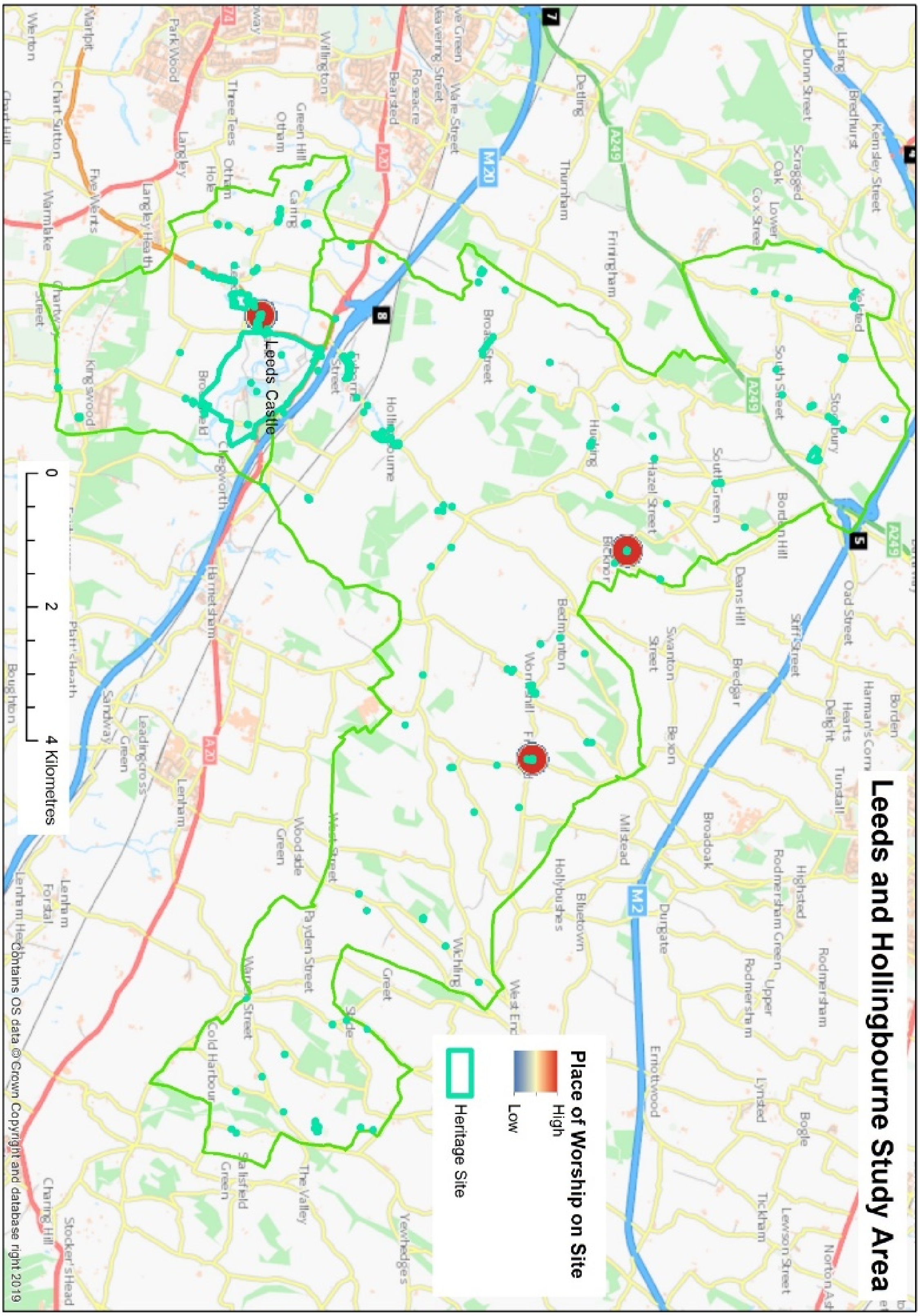

Figure 16 Place of Worship (PoW) in the Leeds and Hollingbourne HAZ coinciding with crime hotspots.

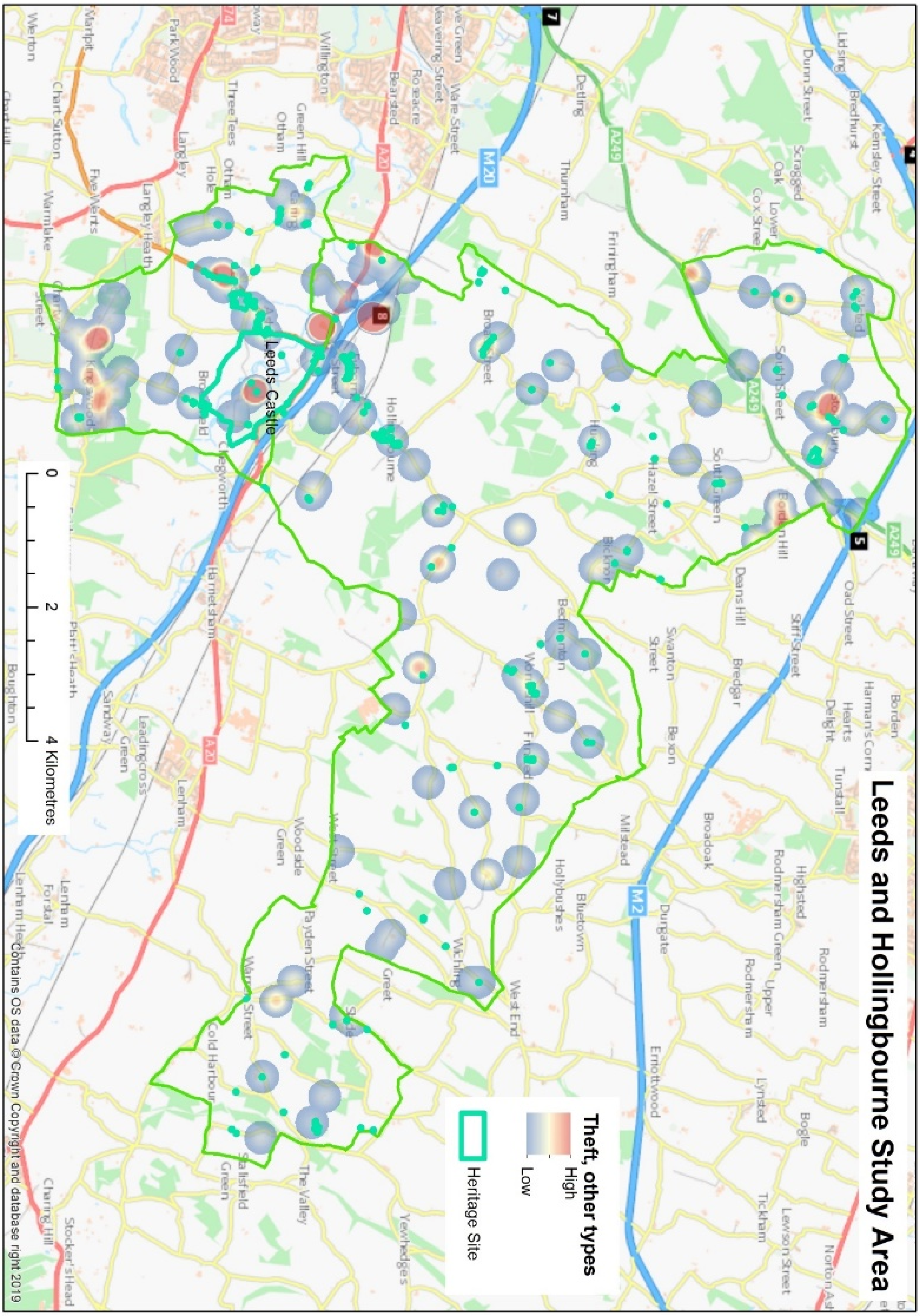

Figure 17 Location of 'theft -other' crimes, Leeds and Hollingbourne HAZ.

7.2.2 Ramsgate Maps

As mentioned above, Ramsgate is the smallest of the three HAZs used in this study and is located entirely within an urban environment. It is also the most densely populated, most deprived (according to the IMD, see above) and has the highest number of listed buildings (343) and places of worship (14). Hence, it possesses the highest density of these features in comparison to the other HAZs.

The geography of the HAZ is also characterised by its high level of accessibility, provided by a network of small streets.

Hence, Figure 18 presents a hotspot map of the HAZ showing the level of crime within the zone as a continuous surface. Apart from some weaker, isolated hotspots, there is a clear concentration of crime towards the south east of the HAZ, specifically, in a linear zone that stretches 400 metres along the harbour end of the High Street and also along King Street. This area covered by this hotspot coincides with the concentration of retail outlets in the town.

The larger scale of the map allows the perimeters of individual heritage sites to be appreciated. Their coincidence with crime hotspots, however, appears sporadic. Although Figure 19 indicates the locations of places of worship within the HAZ, these do not appear to coincide with the concentrations of crime.

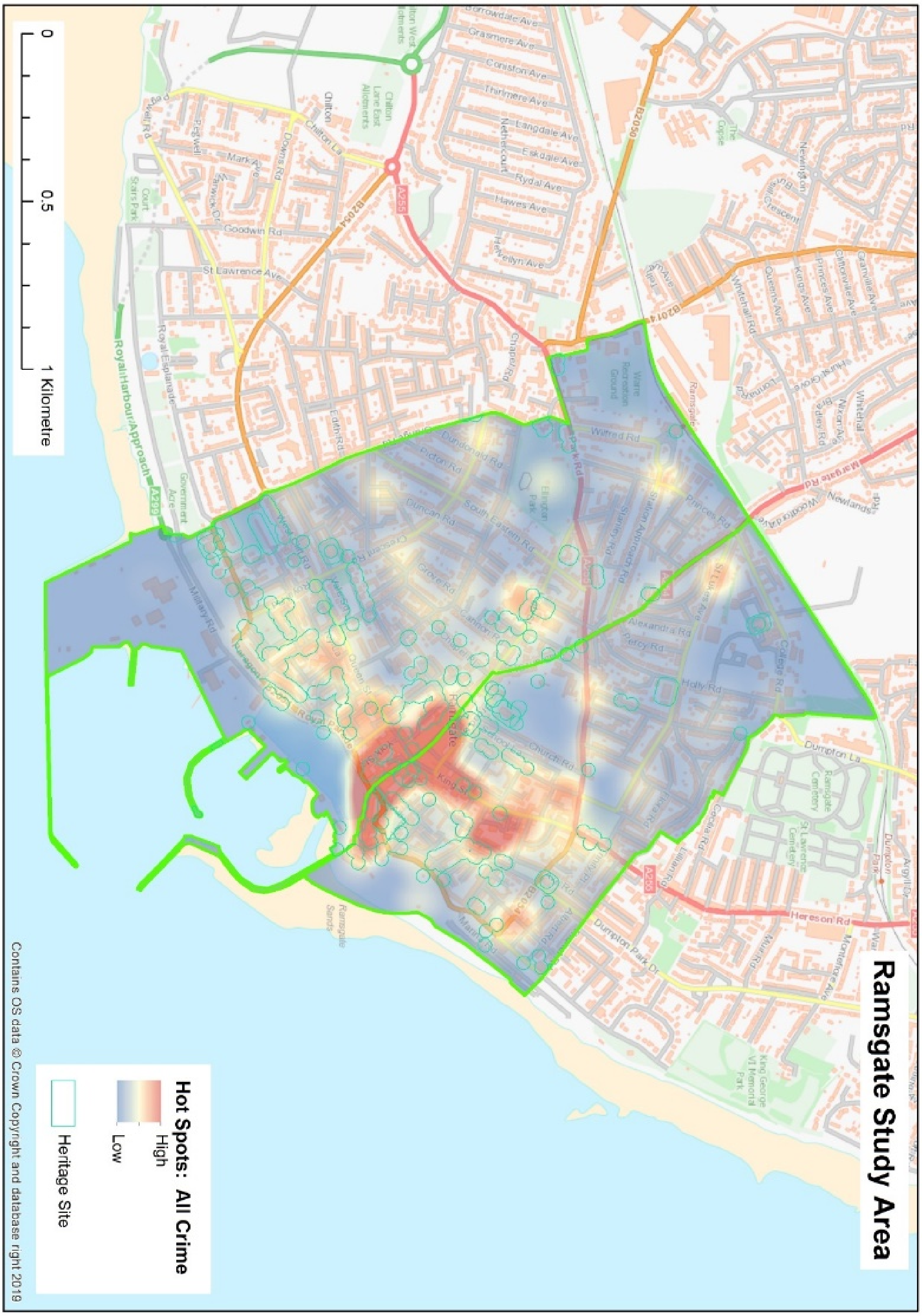

Figure 18 All crime in the Ramsgate HAZ.

Figure 19 Locations of Place of Worship, Ramsgate HAZ.

Furthermore, as Figure 20 shows (as indicated by hotspots of crime within the 'Theft – other category), there is a stronger visual correlation with the spatial pattern of overall crime, for which 'Theft – other' accounts for 18.7% (Table 13).

Although 'Theft – other' accounts for 22.8% of CWACH in the Ramsgate HAZ (Table 16), this is at least partly reflected in the concentration of general heritage sites near or around the hotspot zone identified in the High Street.

From these results, it is difficult to establish whether the introduction of the HAZ has had an impact on heritage-specific crime. The clear concentration of crime located in the High Street and King Street hotspots suggest that heritage-crime occurring in these areas probably have more to do with their proximity to an already-established zone of activity rather than the deliberate targeting of places of worship or listed buildings in the vicinity.

One aspect which is missing for these maps – and hence the HAZ itself – is the Royal Harbour and Marina, since the HAZ is bounded by the coastline. Although these areas do not include listed buildings or places of worship (since they provide mooring facilities for a range of craft), a small number of boats are recognised as historically significant. Their location, outside the limits of the HAZ, will therefore omit any associated crime data and are not plotted on these maps.

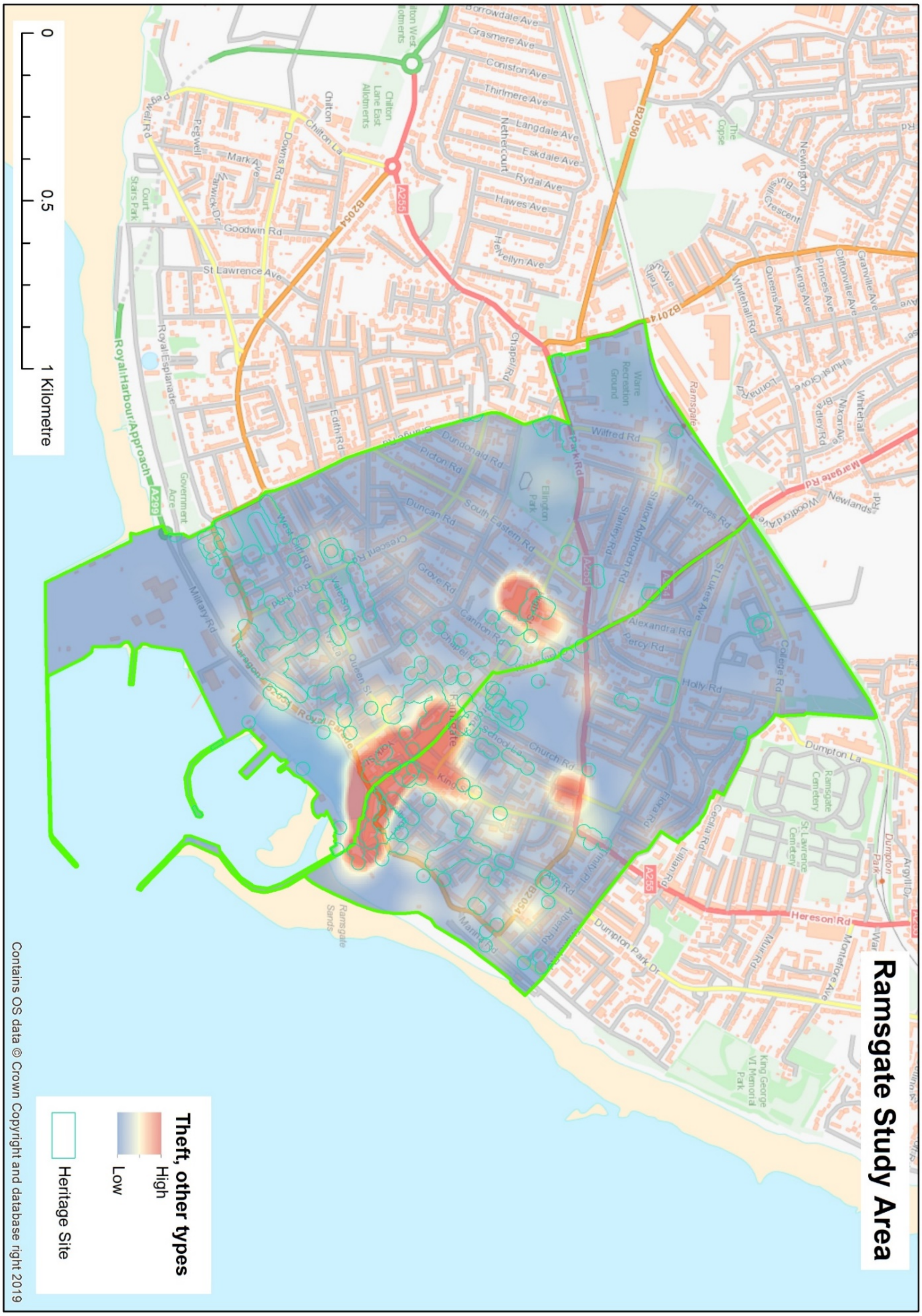

Figure 20 ‘Theft other’ crime hotspots, Ramsgate HAZ.

7.2.3 Swanscombe and Greenhithe Maps

The Swanscombe and Greenhithe HAZ is geographically similar in the presence of a physical boundary (in this case, the River Thames), that limits its northern extent. The HAZ also covers an urban area, although the landscape is very different to that of Ramsgate due to its dissected terrain (usually quarries and water features). These physical boundaries serve to shape accessibility and therefore the location of crime.

Figure 21 is a hotspot map showing the distribution of all crime across the Swanscombe and Greenhithe HAZ. The spatial pattern is unlike either of the other two HAZs, primarily because there are two large (c. 1km radius) zones of crime, centred on Swanscombe and Greenhithe. Each of these essentially covers the developed areas of these urban environments, physically constrained by the quarries to the south, the relatively barren peninsula to the north, and Ebbsfleet International station to the east. (Incidentally, crimes in the vicinity of the station appear to be concentrated in the car park to the north.)

The constricted nature of these two large hotspot areas may change over time as new developments are built on their peripheral zones and access is improved.

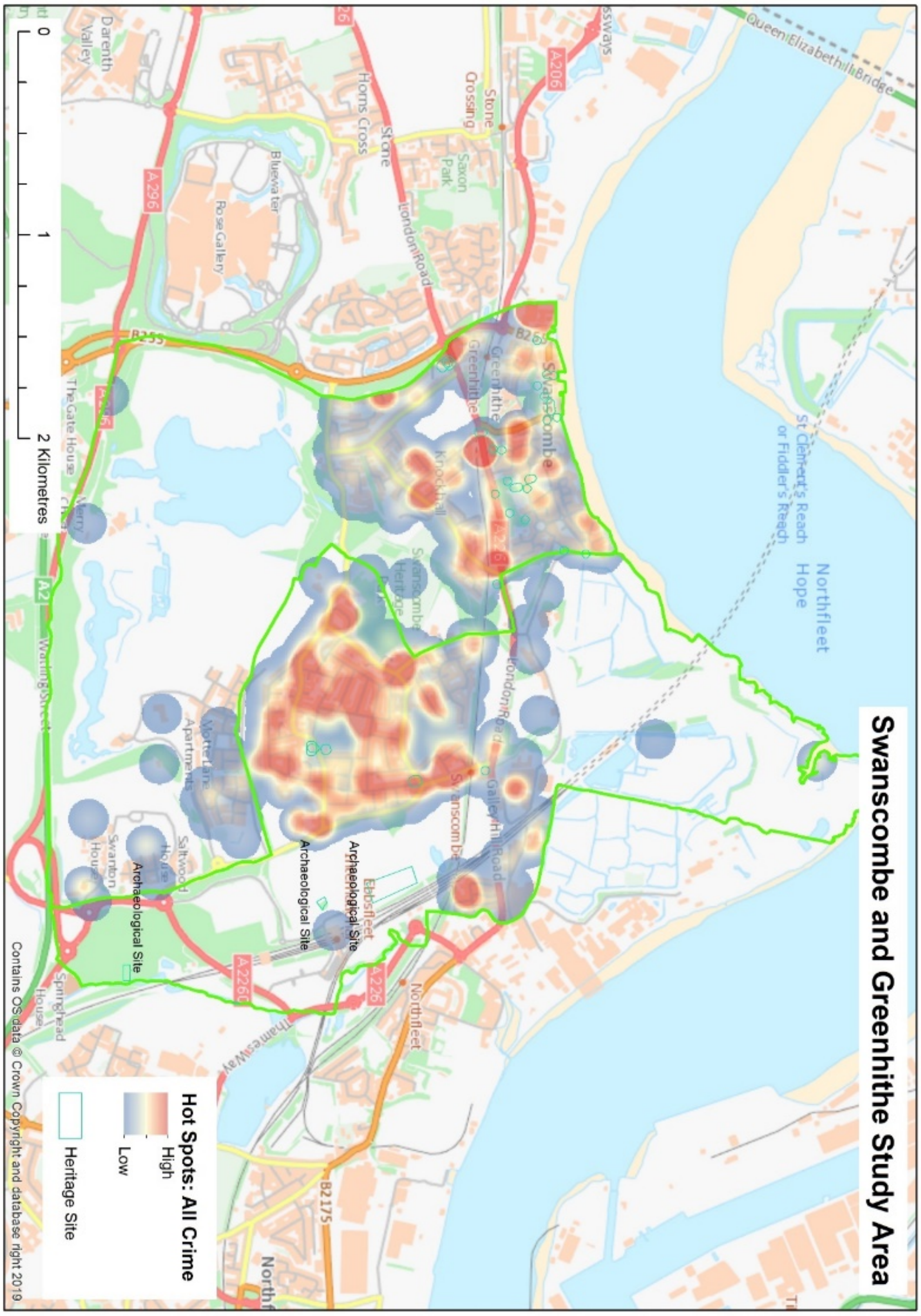

Figure 21 ‘All crime’ hotspots, Swanscombe and Greenhithe HAZ.

Figure 22 shows the places of worship that coincide with crime hotspots. As with the analysis of the Ramsgate HAZ, these are located within an existing area with a concentration of crime and it is therefore difficult to surmise that they have been subject to heritage-specific crimes.

A visual comparison of Figure 21, a hotspot map of all crime with Figure 23, which is a hotspot map of crime falling into the 'Criminal damage' category, suggests a strong association between the two and again does not imply the existence of heritage-specific crimes.

The final map of this series, Figure 24, is a hotspot map of crime falling into the 'Theft – other' category. Unlike the spatial patterns of the previous hotspot maps, this map indicates a pattern within the Swanscombe hotspot on Figure 21 (all crime), where crimes in this category are focused on the area surrounding Swanscombe station.

This HAZ reveals the extent to which hotspots are shaped by physical factors and also how a particular category (Theft -other) has a distinctive pattern of its own within these more general limitations of access.

That the Business Park, lying to the north of Swanscombe, has seen relatively little crime while the major hotspots are confined to the urban areas may suggest that accessibility provides a key to understanding patterns of crime within these HAZs.

Hence, accessibility to places of worship and listed buildings may be a relatively strong factor in assessing their vulnerability. This may challenge the assumption that heritage-specific crime tends to coincide with a remote, inaccessible, and ultimately, rural, geographical environment.

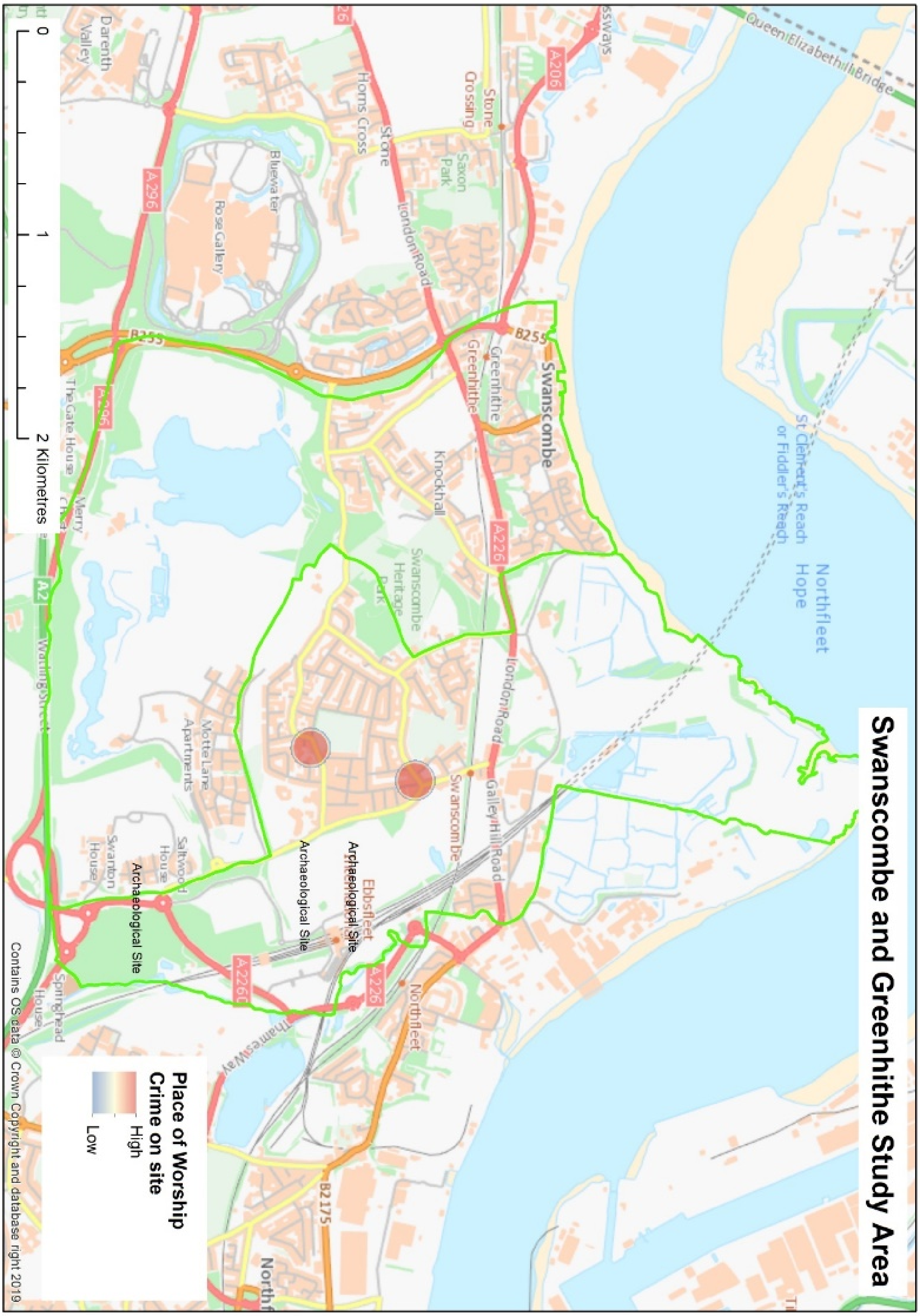

Figure 22 Places of Worship and crime hotspots, Swanscombe and Greenhithe HAZ.

Figure 19

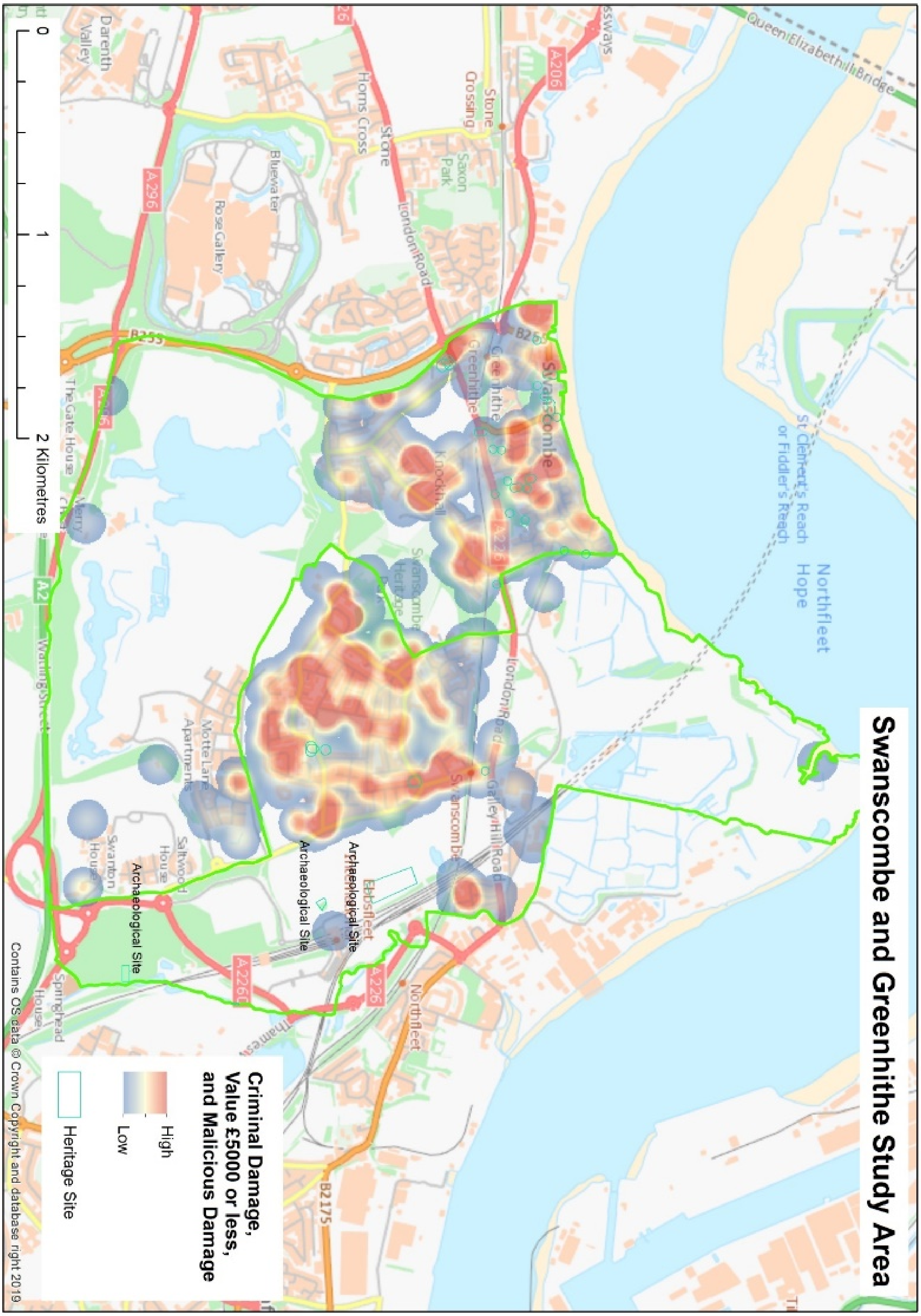

Figure 23 ‘Criminal damage’ hotspots, Swanscombe and Greenhithe HAZ.

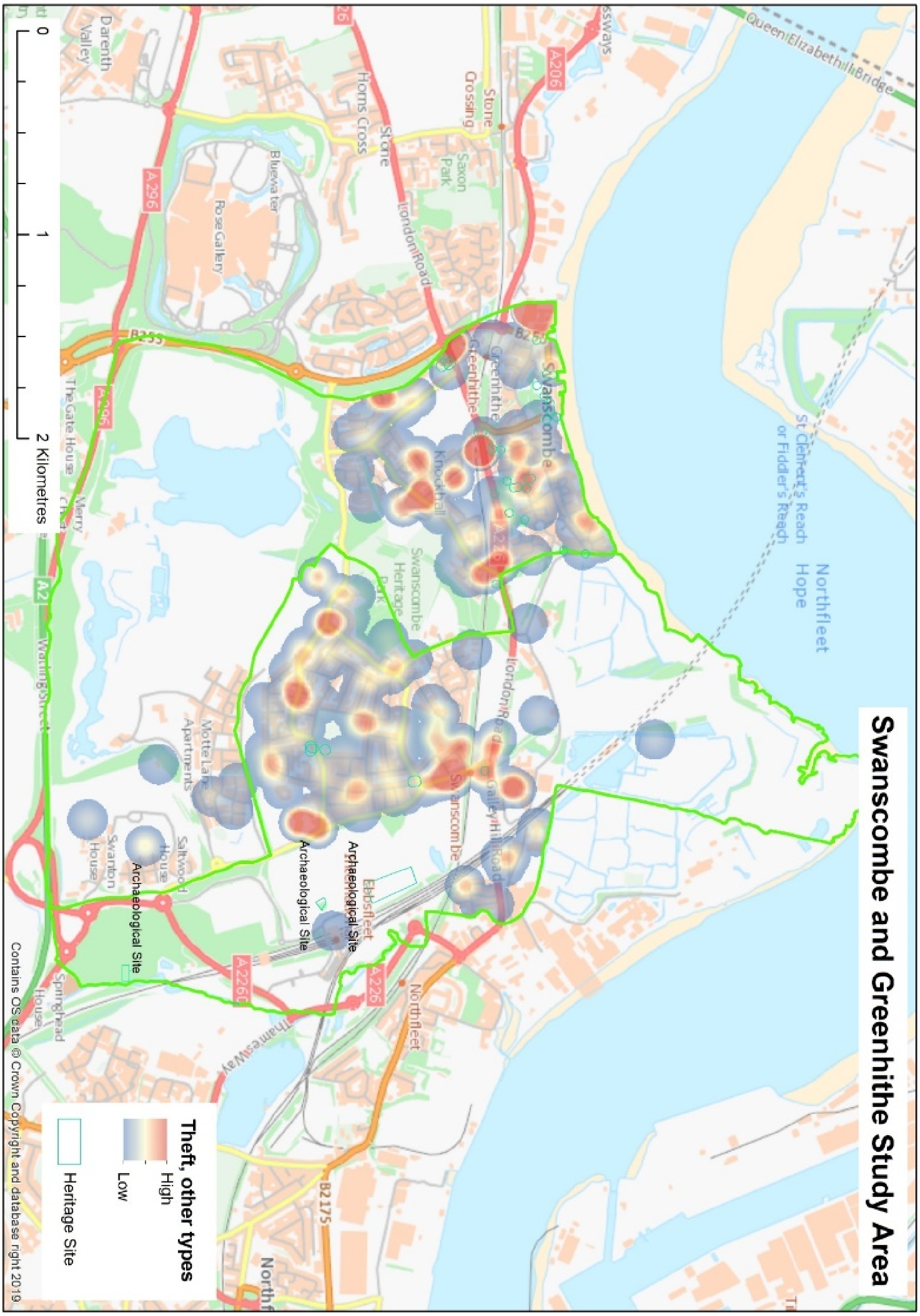

Figure 24 ‘Theft other’ hotspots, Swanscombe and Greenhithe HAZ.

7.3 Temporal analysis of HAZs

In this section of the report we examine how CWACHS in the three HAZs vary according to the day of the week, and the month of the year. We also test for underlying temporal trends, in terms of crime category.

For comparison purposes, Figure 21 below shows the trends in 'all crime' for each of the thee HAZs.

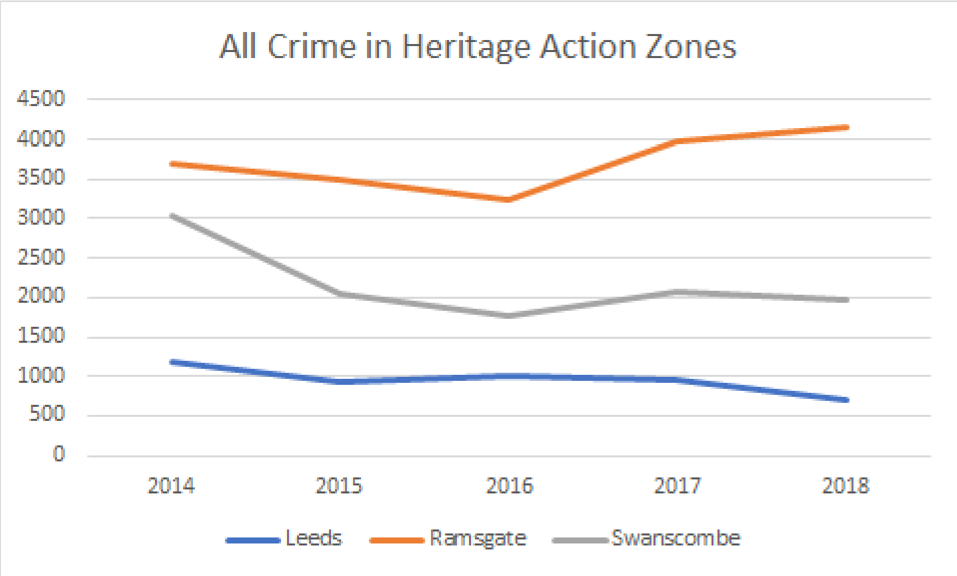

Figure 25 'All crime' in the three HAZs, each year of study.

What is evident from Figure 25 is that numbers of crimes in Ramsgate has grown in recent years, whereas the other two HAZS are relatively stable.

Figure 26 that follows shows the monthly CWACHs totals for each of the three HAZs together with a trend line (for Ramsgate only).

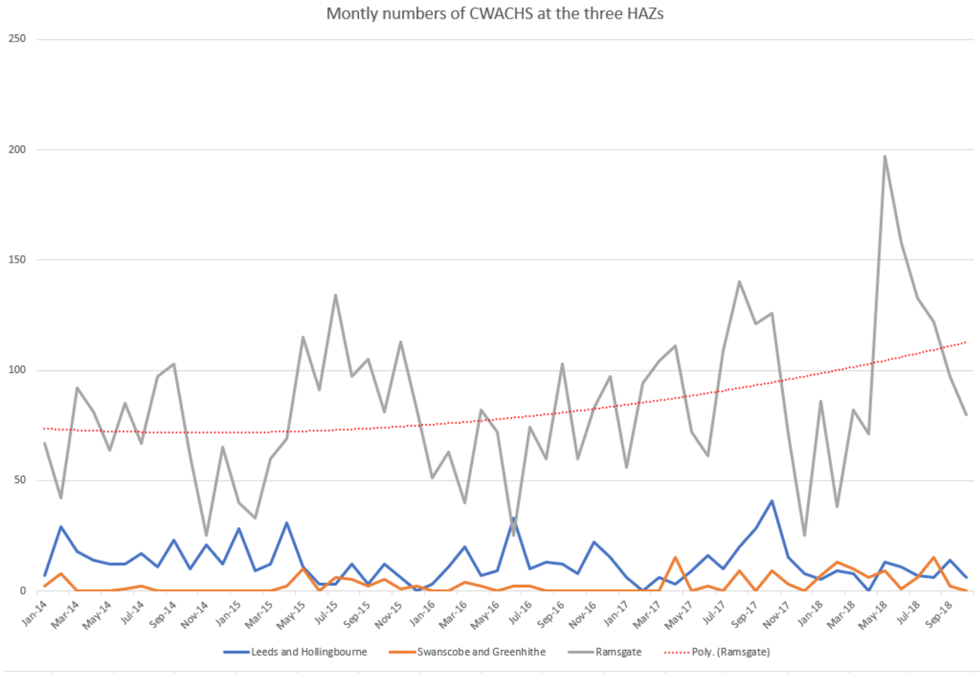

Figure 26 Numbers of crimes each month for each HAZ, together with trend line for Ramsgate.

As Figure 26 demonstrates, there has been an increase in CWACHS within the Ramsgate HAZ. Less certain is a possible increase within the Swanscombe and Greenhithe HAZ (although the numbers are too small to be confident). There does not appear to be a significant increase within the Leeds and Hollingbourne HAZ.

There was no apparent seasonality in the CWACHS data for the three HAZs.

An analysis of time of day for all crime in the three HAZs was conducted and the results are shown in Figure 27 below.

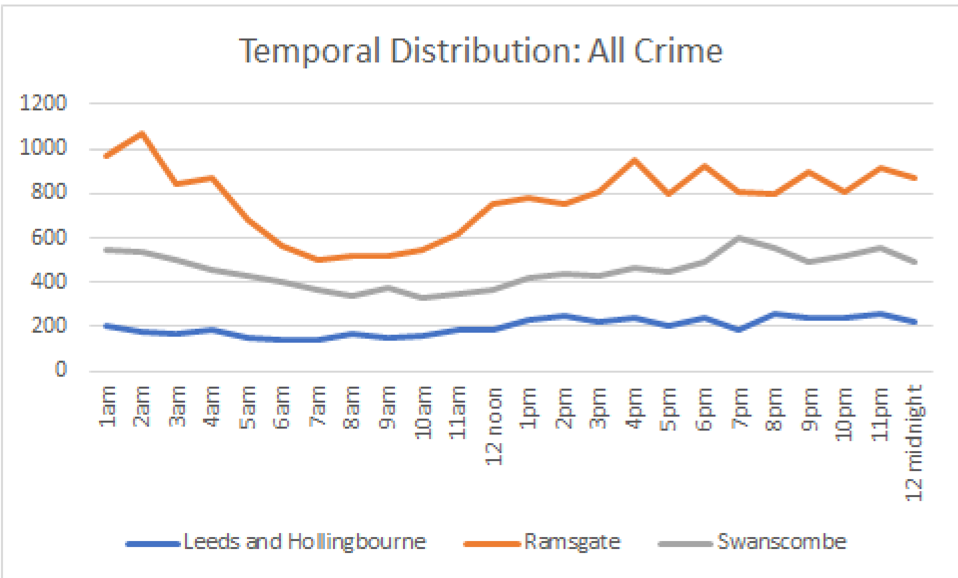

Figure 27 'All crime' daily temporal distribution for the three HAZs, In general terms all crime in the three HAZs follows a similar temporal cycle to that of all crime in Kent and Medway.

Each of the three HAZs were then analysed for the hourly cycle for the CWACHS and the results are shown in Figures 28 and 29. (Together with two of the most commonly occurring CWACHS in each HAZ.)

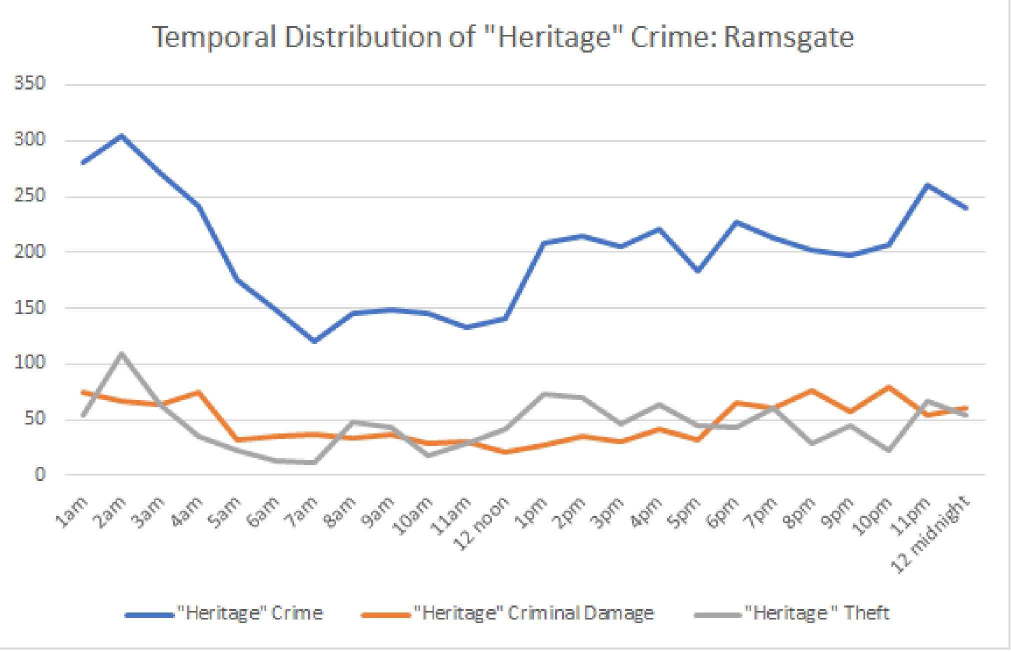

Figure 28 Temporal distribution of CWACHS within the Ramsgate HAZ.

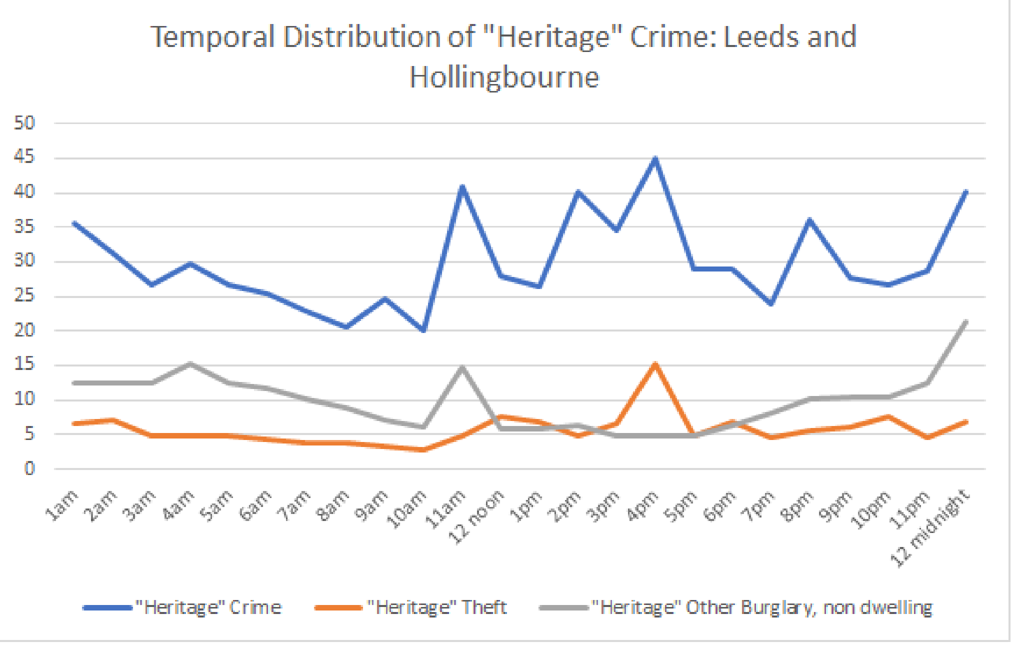

Figure 29 Temporal distribution of CWACHS within the Leeds and Hollingbourne HAZ.

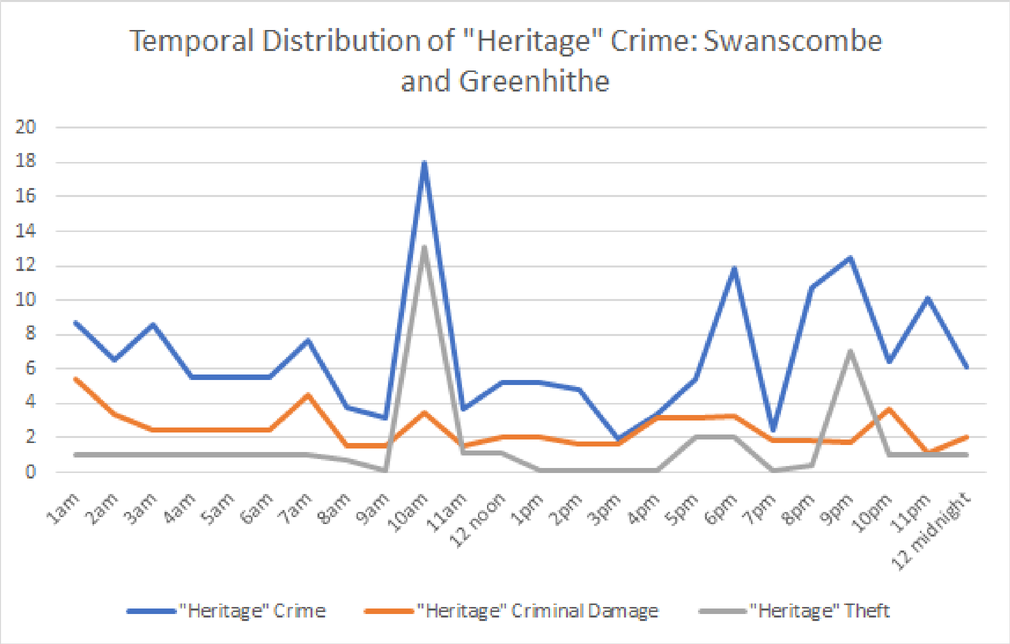

Figure 30 Temporal distribution of CWACHS within the Swanscombe and Greenhithe HAZ.

The Ramsgate HAZ hourly temporal distribution seems unremarkable, following relatively closely that of CWACHS in Kent and Medway as a whole.

Within the Leeds and Hollingbourne HAZ the two most common types of CWACHS are 'theft offences' and 'burglary (non-dwelling)'. Their respective spikes at 4pm and 11am are of potential interest.

In Swanscombe and Greenhithe HAZ there are (perhaps unexpected) local maxima[68] at around 11am and 8pm, but the low totals make interpretation problematic.

7.4 Discussion of results

The three HAZs are very different in both geography and sociodemography. Leeds and Hollingbourne is the largest and most affluent of the three Zones, occupying a sprawling rural area. Ramsgate is the smallest of the three zones, but has the largest population and also the most Listed Buildings and Places of Worship. It is the most deprived of the three Zones. Swanscombe and Greenhithe is a rapidly developing area, and is in the middle of the three zones in terms of measures such as income.

The frequency and spatial distribution of crime follow what is to be expected from the socio-economic and geographical morphology of the HAZs.

Generally, the most prevalent type of crime occurring within the Leeds and Hollingbourne HAZ tends to be burglary, while that within Ramsgate, Swanscombe and Greenhithe tends to be criminal damage or theft. As mentioned earlier, the former HAZ covers a more affluent rural area; the latter two HAZs are urban in character and both have a higher IMD ranking.

[68] 'Local maxima' are sections of a graph which have larger values than the parts which proceed and follow but are not necessarily the maximum value for the complete range.

The coincidence of CWACHS and heritage locations within these areas however suggests that those in rural locations are not targeted any more specifically than those in urban areas. Conversely, the spatial pattern of CWACHS tends to follow the spatial pattern of crime, but this is especially clear within urban areas.

Hence, for locations such as Ramsgate, heritage locations (e.g. listed buildings and places of worship) within and on the fringes of areas of higher crime may be more vulnerable to heritage-specific crime than heritage locations in a rural environment.

This has implications for heritage crime prevention in terms of how urban and rural locations are protected. The results do, however, imply that there is no evidence of an impact of the introduction of HAZs on the occurrence of CWACHS. This suggests that the strategy may need to be reconsidered.

8 Heritage crime at Places of Worship, Kent and Medway

It became evident during the course of the research for this report that heritage crime at Places of worship (PoWs) in Kent and Medway required a more in-depth analysis. For example, the proportion of PoWs experiencing a crime seems high when compared to all listed buildings and to scheduled monuments.

It is also the case that churches in particular appear to have been badly affected by metal theft crime in recent years, with one survey in 2019 (conducted by VPS Security Services) finding an average of 37 incidents of metal theft each month from churches in the UK in year ending April 2019 (VPS, 2019).

8.1 Frequency analysis

There were a total of 12,848 CWACHS committed at or within 20m of a Place of Worship[69] (PoW) during the period under study, averaging at approximately 2,660 per year. This represents 13.4% – a significant proportion of all CWACHS[70].

Of these CWACHS, 4,101 (32%) were located within the PoW or were associated with the outer fabric of the PoW, averaging about 850 per year for all 1,197 PoWs included in the study (approximately 70%[71]).

However, in order to gain an estimate of the proportion of heritage-specific crime within this subset, a true random sample of 150 crimes were made and a manual inspection of crime reports conducted[72].

It should be noted that there are a number of possible errors in this undertaking, all of which have a bearing on the reliability of any estimates derived from the sample.

In the sample of 150 crimes, 36 (24%) were located within a PoW or involved the fabric of the building. These were broken down into 'Theft -other' (15; 42%); 'Burglary'[73] (10; 28%), 'Criminal Damage' (10; 28%), and 'Hate incident' (1; 3%).

Of the remaining 114 (76%) CWACHS that were close to but not within a PoW, very few could be considered heritage crimes. These mainly consisted of criminal damage e.g. to tiles on roofs of outbuildings.

Ten of the CWACHS that were located within the PoW or were associated with the outer fabric of the PoW were 'heritage specific crimes' (mostly criminal damage to windows and theft of metal or historic objects). Hence whilst only approximately 7%[74] of CWACHS committed at or within 20m of a PoW were targeted heritage crimes[75], this rose to approximately 28%[76] for CWACHS that took place within or to the outer fabric of the PoW.

[69] The vast majority of these were churches of Christian denominations.
[70] This is especially relevant, given that PoWs usually comprise buildings rather than comparatively large geographical spaces such as Conservation Areas
[71] Note that this is based on total numbers of crimes. Clearly some PoWs will experience repeat victimisation, others none whatsoever.
[72] Undertaken by a Kent Police analyst in a secure setting.
[73] Both 'domestic' and 'non-domestic'.
[74] A 95% confidence interval of 2.7% to 10.7%.
[75] Interestingly, the same estimated proportion as with all heritage sites.
[76] A 95% confidential interval of 20.9% to 35.1%.

As noted earlier, metal theft from churches has been of particular concern. Hence, we also conducted an analysis of this specific form of crime at or within a PoW.

The methodology employed was to formulate search criteria of the Kent Police data crime records for theft property type as 'metal'[77] both infrastructure and non-infrastructure related, with the location code being a 'place of worship' (as defined by Kent Police analysts, which includes churches, synagogues and mosques[78]). Note that this method identifies metal theft from within or on, a PoW and not those close to it.

For the period of study this indicated a total of approximately 105 recorded crimes of metal theft from within or from the fabric of PoWs, giving an average of approximately 22 per year.

Further analysis of trends in metal theft from PoWs in Kent and Medway may be found in section 8.4 of this report.

8.2 Temporal analysis

In this section of the report we analyse the underlying trends of CWACHS at Places of Worship and variation according to the time of day.

Table B1 (in Appendix B) below shows the numbers of CWACHS at PoWs for each month from January 2014 to October 2018.

A time series graph of of these data was constructed, and a trend line constructed (using the Prophet trend line as a guide) and the result is shown in Figure 31 below.

[77] Note that under Home Office rules, for 'flagging' purposes, 'offences should be flagged as Metal Theft if the police employee filing the crime report believes that the intent for committing the offence was to remove the item for its scrap metal value rather than the acquiring of the item (s) (Home Office, 2019, p.3).

[78] The Kent Police meaning of 'place of worship' is very close to that which appeared to be used by Historic England. We used the Historic England spatial data in other parts of this report.

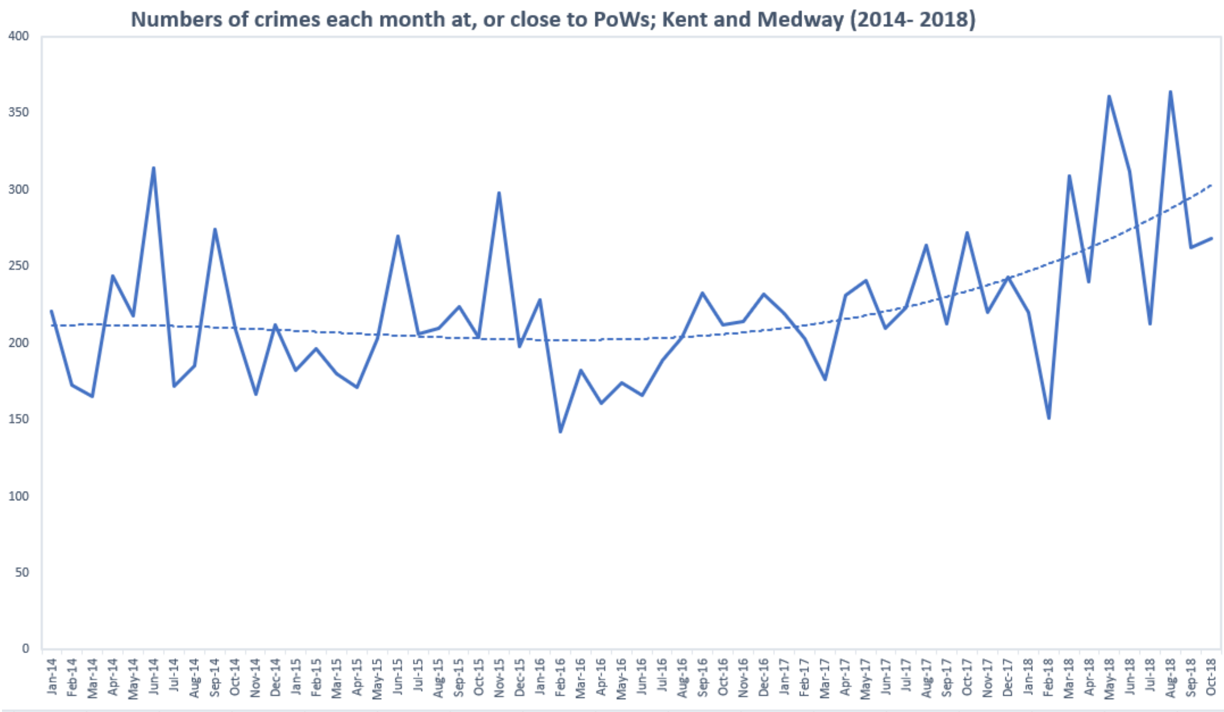

Figure 31 Numbers of crimes each month, PoWs, Kent and Medway

The curve of best fit[79] shows an underlying trend of a significant increase of CWACHS at PoWs since around summer 2016. The rate of increase of CWACHS appears higher than that of all crime in the same period.

Indeed, PoW crime numbers for August 2018 (364) are almost double that of August 2014 (185) and approximately 2.5 times the lowest figure of 142 for February 2016.

In terms of seasonality, we attempted to assess this by constructing and examining monthly crime as the proportion of annual crime at Places of Worship. This is shown in Figure 32 below.

[79] In this case a polynomial of degree two.

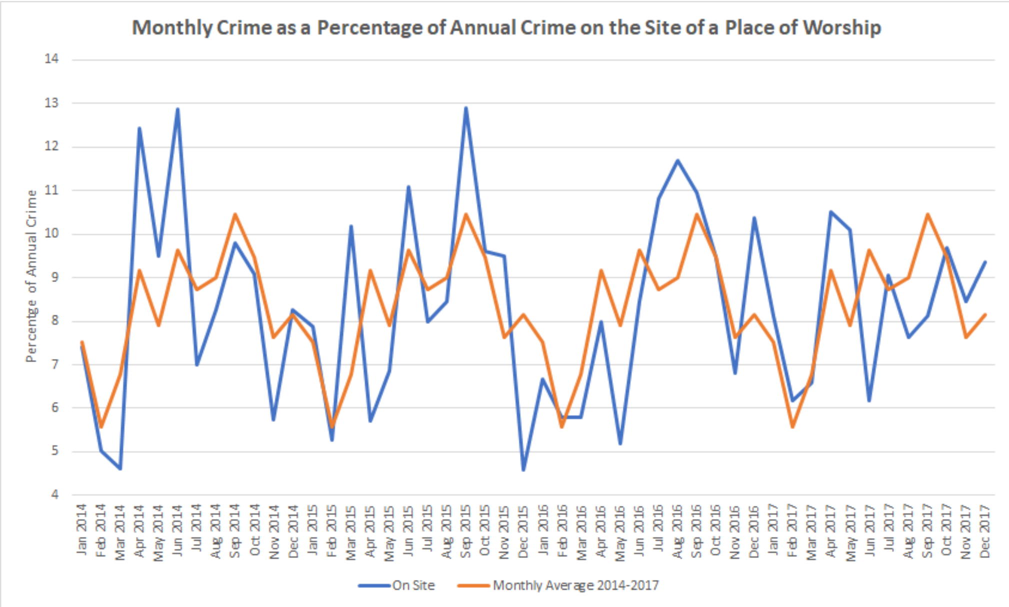

Figure 32 Monthly crimes at PoWs, Kent and Medway as proportion of all crime.

There are distinct dips in February, May and November, with highs in April, June and September. Note that this pattern is somewhat different to that of overall crime in Kent and Medway.

Figure 33 below was to inform an analysis of the time of day of CWACHS at PoWs. It shows the daily temporal distribution of all CWACHS together with totals for a number of crimes that make up the total.

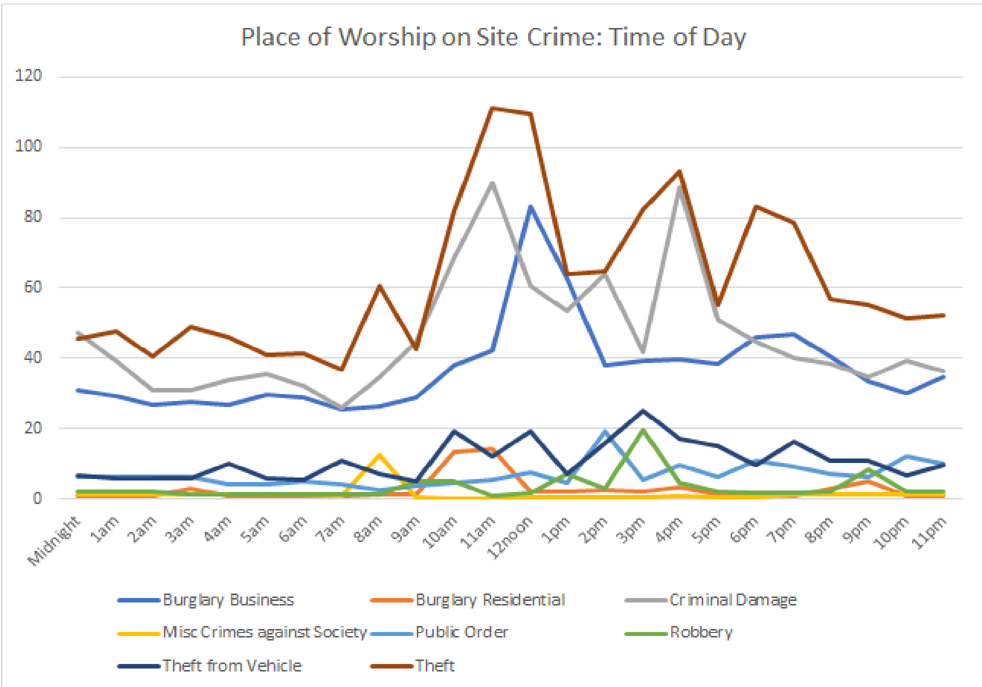

Figure 33 Temporal distribution PoW crimes by time of day, Kent and Medway.

The timing of Place of Worship crime, shown in Figure 29 below, differs significantly from the usual distribution of all crime in Kent and Medway (see Figure 4 in section 6.1.4). The CWACHS at PoWs instead peak in frequency at about noon, with further (but less pronounced) peaks at about 4pm and 7pm.

8.3 Association with road network and urban density

The theft of lead from church roofs requires the offenders to have means to transport stolen metal from the PoW to other locations, and the existence of a target. It follows that there may be some association between the vulnerability of a PoW to crime, the road network and urban density.

To test this, we devised a 'Persistence of Crime Score' This uses a rating of 1 to 5, indicating how many of the five years of study each site was exposed to crime, so a rating of 1 indicates that crime has occurred in a location during one of our study years, while a rating of 5 indicates that crimes have occurred there during all five of the years.

Figure 34 below gives an example of road classification for a part of Kent.

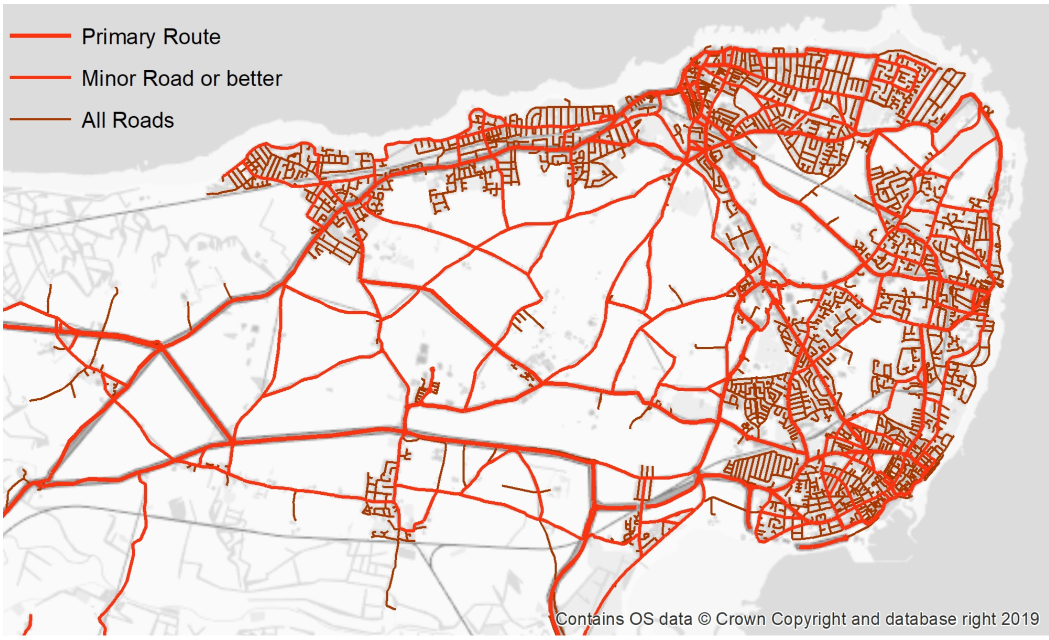

Figure 34 Road density map for part of the Ise of Thanet, Kent.

The various road variables were calculated using the density of each level of road within the specified distance of each Place of Worship, based on OS OpenData - Local. The 'All Roads density' included the Minor Roads and Primary Routes, while the Minor Road density also included the Primary Routes.

Urban density was calculated using the amount of buildings within the specified distance of each Place of Worship, based on OS OpenData - Local.

Table 17 below gives the Persistence of Crime Score for PoW CWACHS.

	Persistence of Crime Score (within 20m)	Crime (within 20m)
Urban Density 100m	0.472	0.331
Urban Density 250m	0.491	0.315
Urban Density 500m	0.489	0.311
All Roads Density 100m	0.438	0.267
All Roads Density 250m	0.486	0.317
All Roads Density 500m	0.482	0.311
Minor Road or better Density 100m	0.084	0.029*
Minor Road or better Density 250m	0.249	0.194
Minor Road or better Density 500m	0.334	0.251
Minor Road or better Density 1km	0.359	0.258
Primary Route Density 100m	0.219	0.133
Primary Route Density 250m	0.312	0.240
Primary Route Density 500m	0.374	0.299
Primary Route Density 1km	0.399	0.292
Primary Route Density 2.5km	0.386	0.251

Table 17 Persistence of crime scores around PoWs by route density, Kent and Medway.

With over 1,000 sample sites, the critical value is 0.082 at the 99% confidence level. Only one of the above is not statistically significant, indicated by *.

Table 18 below is for the subset of CWACHS which are within the PoW (‘on site’).

	Persistent Crime Score (On Site)	Crime (On Site)
Urban Density 100m	0.160	0.115
Urban Density 250m	0.219	0.180
Urban Density 500m	0.234	0.195
All Roads Density 100m	0.158	0.119
All Roads Density 250m	0.211	0.176
All Roads Density 500m	0.235	0.198
Minor Road or better Density 100m	0.020*	0.001*
Minor Road or better Density 250m	0.097	0.083
Minor Road or better Density 500m	0.152	0.125
Minor Road or better Density 1km	0.159	0.132
Primary Route Density 100m	0.108	0.093
Primary Route Density 250m	0.133	0.136
Primary Route Density 500m	0.177	0.169
Primary Route Density 1km	0.192	0.177
Primary Route Density 2.5km	0.193	0.171

Table 18 Persistence of crime (within site) scores around PoWs by route density, Kent and Medway.

The Critical Value is the same, and although the correlation coefficients are lower, only two are not statistically significant at the 99% confidence level.

Figure 35 that follows shows diagrammatically the Persistence of Crime scores around Places of Worship in Kent and Medway.

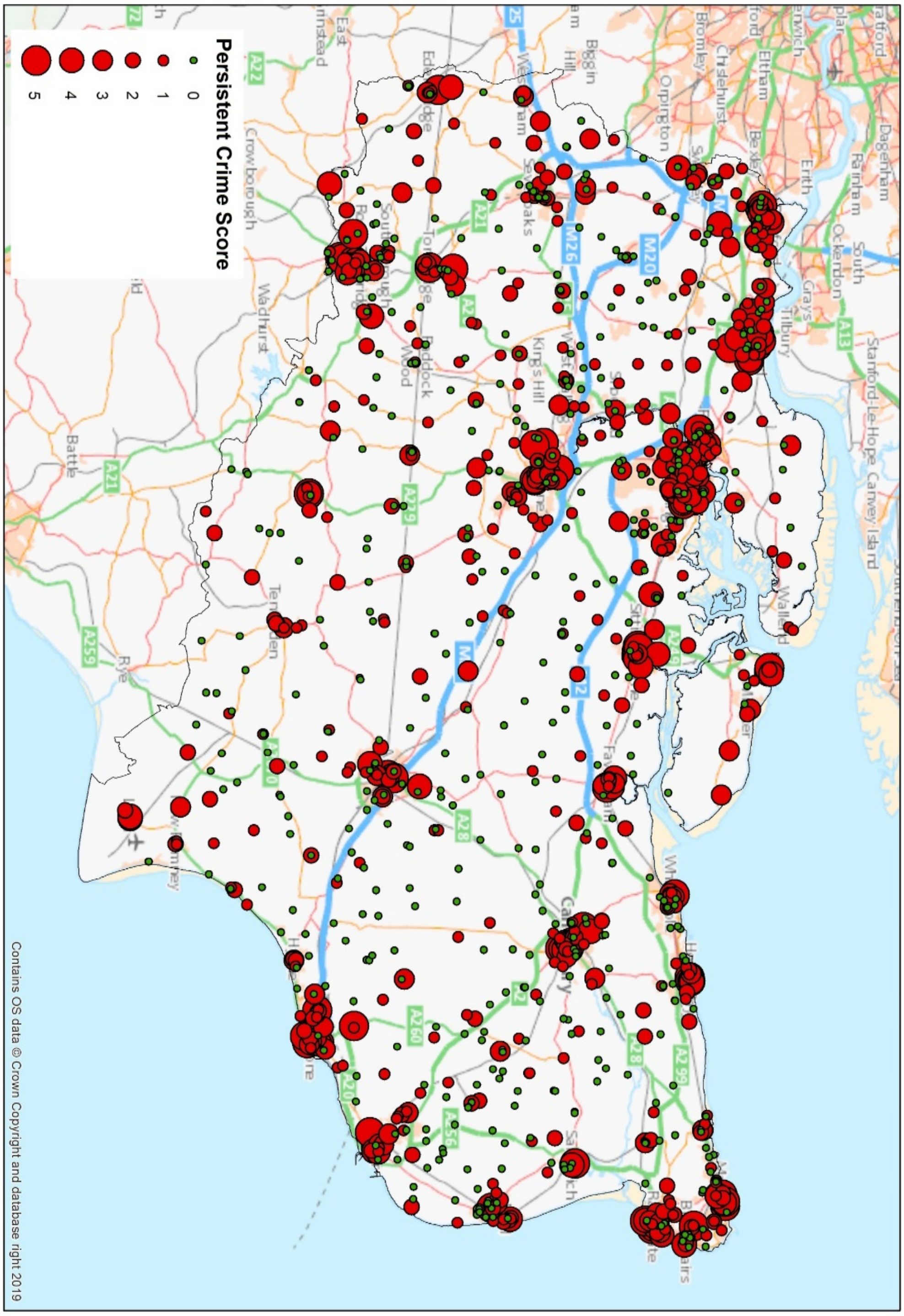

Figure 35 Persistence of crime scores, PoWs, Kent and Medway.

Place of Worship crime showed statistically significant correlations with urban density and the density of different types of road within various distances. The above would seem to suggest that Places of Worship are more likely to experience crime if they are in built up areas and/or have good road access.

8.4 Metal theft from PoWs and association with scrap metal prices

As noted earlier, as part of the research for this report we analysed Kent Police recorded crime data concerning theft of metal from within, or on a place of worship for the period under study.

Note that in what follows 'metal thefts' includes other crimes, other than the theft of lead from the roof of a church in Kent and Medway. As Ecclesiastical Insurance Group explain: 'lead, copper and stainless steel roof coverings, including bay window roofs and roof flashings, copper lightning conductors, lead and copper rainwater pipes, bronze statues, metal garden ornaments, iron gates and even church bells have all been stolen' (Ecclesiastical Insurance Group, 2017, p.1).

During the period of study there were a total of 105 recorded thefts of metal from Places of Worship in Kent and Medway. Table B2 (in Appendix B) below shows the monthly frequencies.

The Prophet forecasting tool was used to test for seasonality and the results[80] shown in Figure 36 below.

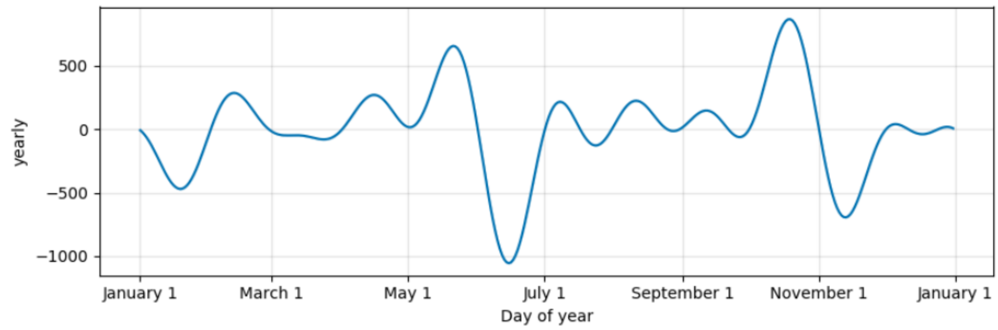

Figure 36 Test for seasonality for metal thefts from PoWs, Kent and Medway.

As Figure 36 illustrates, there is weak evidence of a 6-month period between peaks and troughs (metal thefts appear to peak during the early autumn around mid-October and trough in the early summer, around mid-June).

The same Prophet forecasting tool was used to identify any underlying trend and this was used to help construct the time series and underlying trend line shown in Figure 37.

[80] Results should be treated with caution given the relatively small frequencies involved.

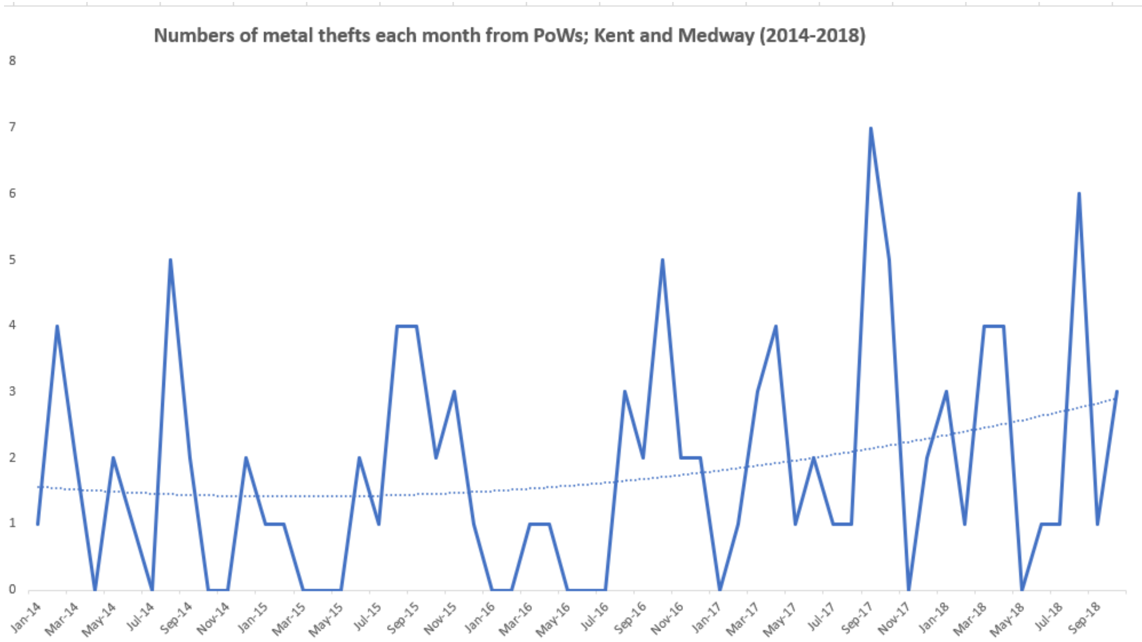

Figure 37 Monthly totals of Metal thefts from PoWs, Kent and Medway with trend line.

There are clear indications of a significant increase of metal thefts from PoWs in Kent and Medway, with the increase probably beginning at about Summer 2015.

Previous research has shown a correlation between metal theft and scrap metal prices[81]. We therefore investigated whether the increase in metal theft from PoWs in Kent and Medway was correlated[82] with scrap metal prices.

Scrap metal prices were accessed from the 'letsrecycle.com[83]' website[84]. Table B3 (in Appendix B) shows lead and mixed brass prices for each month of the period of study.

The results were that there was a statistically significant correlation with both the price of mixed brass prices (0.79) and with lead prices (0.88) when calculated as a 12-month moving average. This is also illustrated in Figure 38 below.

81 Sometimes referred to as the 'Price-Theft Hypothesis' (Sidebottom et al., 2014).
82 As noted earlier in the report, the existence of significant statistical correlation between two or more variables does not necessarily indicate cause and effect.
83 Part of the Environment Media Group Ltd.
84 As explained by the company concerned, 'letsrecycle.com provides a monthly guide to scrap metal prices in the sector, drawing on input from a range of businesses in the scrap metal recycling industry' (letsrecycle.com, 2020).

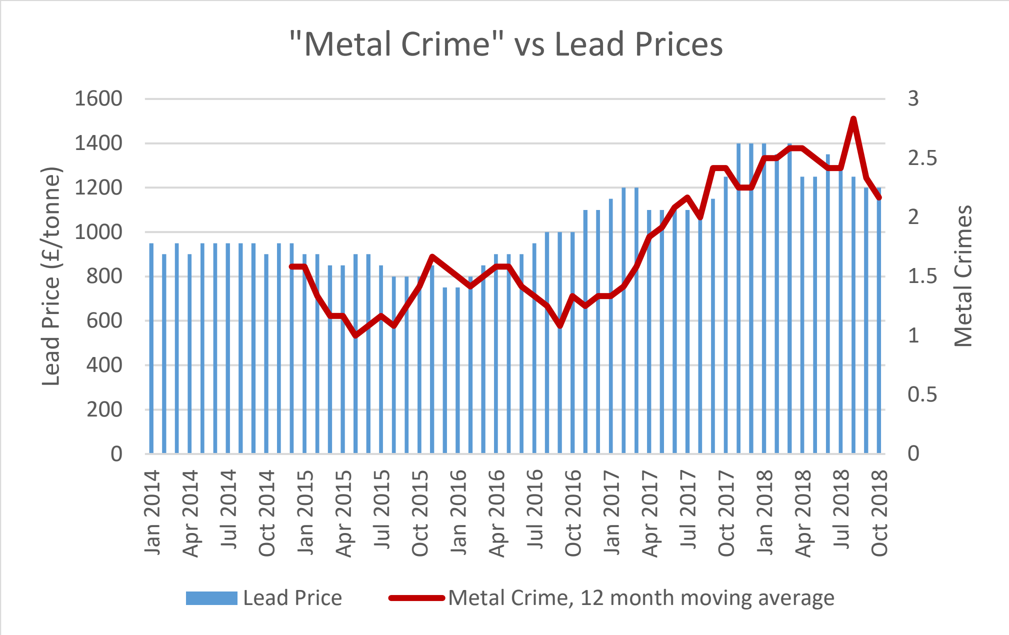

Figure 38 Association between metal thefts from PoWs, Kent and Medway and average lead prices.

However, when we conducted further research, we found one other offence correlated highly with scrap metal prices – that of 'public order offences' at heritage locations (0.79).

8.5 Discussion of results

Crimes within, at or close to Places of Worship (PoWs) in Kent and Medway constitute a significant proportion of all crimes at heritage locations, averaging about 850 per year, for the 1,197 PoWs studied. Approximately 32% of the crimes were located within the PoW or were associated with the outer fabric of the church. The remainder were close by.

PoWs are experiencing increasing numbers of crimes, and this has been particularly the case since around summer 2016. The rate of increase appears higher than that of all other crimes in the same period, both in general and at other heritage locations.

Within PoWs, only a very small proportion of crimes were targeted heritage crimes (about 7%) but this proportion rises significantly (to about 28%) if the fabric of the building is also included in the analysis.

PoWs in Kent and Medway are more likely to experience crime if they are in built up areas and/or have good road access.

In terms of metal theft from PoWs, there were approximately 22 for each year of study. However, there is clear statistical evidence that metal thefts from churches have been increasing since around summer 2016. The rate of increase appears higher than that of most other crimes.

The temporal pattern for metal thefts from PoWs also differs from that of all crime, as do the times of day at which they occur.

Finally, there is a statistically significant correlation with both the price of mixed brass prices and with lead prices during the period of study (which was after the Scrap Metal Dealers Act 2013).

9 Comparison with 2012 'Bradley' (Historic England) report

The only other major study that included a data analysis of the prevalence of heritage crime in regions of the UK that we are aware of is the Bradley et al. (2012) report cited earlier.

In this section of our report we compare some of the 'Bradley' findings with the outcomes of our own research. A summary is shown in Table 22 below.

Where differences are noted this could, of course, be due to a number of reasons including the time period that has elapsed, differing definitions and so. It is also the case that our methodology does not allow for a direct comparison with some of the Bradley findings, such as those for Conservation areas.

'Bradley' question/findings	'Bradley' findings	Our findings
How prevalent is heritage crime in different types of area?	Heritage assets located in central urban areas face the risks common to all buildings in such areas.	Our research appears to confirm this.
	In areas with few heritage assets (e.g. many deprived areas), assets face higher heritage crime risk.	The HAZ analysis confirms this in terms of a greater risk in economically poorer areas.
What type of heritage crime is most prevalent?	Criminal damage makes up the bulk of all heritage crime.	'Theft offences' were the most frequently occurring in our study, 'criminal damage' second to this. However, 'theft offences' covers a wide range of theft-related crimes whereas 'criminal damage' is more homogeneous.
	The risk of criminal damage to heritage assets is substantially greater in more deprived areas.	Our analysis of the three HAZs lends some support to this.
	The frequency of metal theft warrants separate consideration.	Our research demonstrates that this is still the case.
What types of heritage asset are most affected by crime?	Criminal damage is the main heritage crime risk for Listed Buildings and in Conservation Areas.	Unable to say but criminal damage certainly featured highly in the crimes within Conservation Areas and at or close to Listed Buildings.
	Variation in overall heritage crime risk was slight between most heritage asset types.	Our research found significant differences in the heritage locations we studied but our methodology was very different.

	Damage by owners due to unauthorised changes is a non-trivial element of the total picture.	Unable to compare as the information was not available in the Kent Police NCRS.
	Metal theft is not a great risk to buildings in Conservation Areas that are not individually designated.	Unable to compare.
	Scheduled Monuments are different to other heritage assets, in being at rather low risk of metal theft and criminal damage, and higher risk of other crime such as unauthorised metal detecting.	Our research did not find this in terms of criminal damage, but we were unable to measure illegal metal detecting.
What is known about links between socio-economic trends and recent trends in heritage crime?	It appears that metal theft is a growing problem, and this is linkable to wholesale metal price trends.	Our research indicates that this is still a problem, at least in Kent and Medway.

Data findings	18.7% of all listed buildings were physically affected by crime in the previous year.	Our figure is 18.6%, remarkably close.
	The biggest single threat was metal theft with6.7% and 5.2% of grade I/II* and grade II buildings respectively affected by this problem.	Our research also shows that 'theft other' is a frequently occurring crime for listed buildings in Kent and Medway.
	Listed churches and other religious buildings are by far the most at risk, with about 3 in 8 (37.5%) being damaged by crime in the previous year.	Our figure for PoWs is 25.7% - this higher than other heritage locations, but somewhat smaller than 37.5%.
	Metal theft from religious buildings is a particular problem with 14.3% affected.	We agree, metal theft is a particular (and growing) problem.
	Scheduled monuments are affected in different ways to listed buildings. Metal theft us understandably less of a problem at 3.5% per year affected.	Our research found this remains the case in general terms.

	Criminal damage to scheduled monuments is also less at 7.1% compared with around 15% for listed buildings. Scheduled monuments are, though, subject to a greater threat from activities associated with open land, such as unlicensed metal detecting and unauthorised access by off-road motorbikes and cars.	Our rates for criminal damage at scheduled monuments were higher at 12.4%. However, it remains the case that this is lower than that for listed buildings (17.8% in our research).
	The survey compiled insufficient data for robust estimates of the impact on registered parks and gardens, but what was obtained suggested, perhaps unsurprisingly, that they may be the worst affected of all heritage assets.	Our research confirms that Registered Parks and Gardens remain amongst the worst affected of heritage sites (second only to Conservation Areas, which are larger in geographical size).

Table 19 Comparison between the Bradley et al. (2012) and the parallel outcomes of the research for this report.

10 Using Machine Learning to forecast heritage crime

As part of our research for this report we undertook a machine learning (ML) analysis that included the full 'all crime' Kent Police dataset (in excess of one million entries) and the CWACHS locations.

In order to test the feasibility of ML to help prevent heritage crime, in a more manageable way, we looked at CWACHS at PoWs in Kent and Medway as a specific example.

10.1 Machine Learning

In essence, 'machine learning' (ML) is providing machines (i.e. PCs) with the ability to experientially learn without programming them explicitly (Samuel, 1959) usually in order to facilitate 'the automated detection of meaningful patterns in data' (Shalev-Shwartz and Ben-David, 2014, p.xv).

Machine learning allows for the analysis of datasets that are too large for humans to feasibly analyse. It enables the detection of patterns invisible to humans and aids in the reduction of subjectivity in the analysis of data (Pentreath, 2015, p.39).

Machine learning involves inductive inference, that is examples related to a phenomenon are extracted from data and these are used as input to an algorithm which aids in inferring a general model. One aim for a machine learning algorithm could be to learn from data is to adapt its actions to make more accurate predictions[85] as a result (Marsland, 2015).

It should be noted that machine learning does not provide 'explanations' for why particular data sets and algorithms prove to be important in helping to predict; nor does an inferred correlation between variables imply cause and effect.

10.2 ML and preventing heritage crime

Within a crime prevention context, machine learning has been used in a number of ways, including the prediction of serial crimes (Liao, 2010), racist tweets (Burnap & Williams, 2015) and geographical prediction of crime within a city (Kim, 2018). Machine learning is also used for the detection of fraud.

The potential benefit of machine learning for preventing targeted heritage crime is that it allows the creation of predictive models, so if there are sufficient data machine learning could possibly derive a model which estimates the likelihood of a criminal event at a heritage site based on previous criminal activity.

For example with the data available for this research it proved possible to use machine learning to predict the type of crime category that might occur in a location

[85] For example, prediction of targeted heritage crime locations and times.

given the location's geographical coordinates on a particular day of the week (see below).

In addition, with more extensive data it might be possible, for example, to predict which heritage sites or regions are more likely to experience crime on certain days of the week, or perhaps even within particular timeslots.

10.3 Setting up the ML PoW heritage crime model

Machine learning allows for the prediction of a dependent variable, y, based on the values of a set of dependent variables or **features**. Since there are many such features, they are denoted by a capital X. The features used for this research[86] were: Year, Month, Week, Dayofweek, POW, Easting and Northing, where Year, Month, Week, Dayofweek are temporal aspects of the crime committed date.

It was assumed that the committed date was the midpoint between Committed and Committe_1, the two times and dates recorded by Kent Police as lower and upper bounds to the time the crime was committed. Since this is a very imprecise measure of the time that the crime was committed, no temporal data below the level of Dayofweek was used.

As the following correlational heat map shows (Figure 39 below), there is very little correlation between the features, a quality desirable in the application of machine learning.

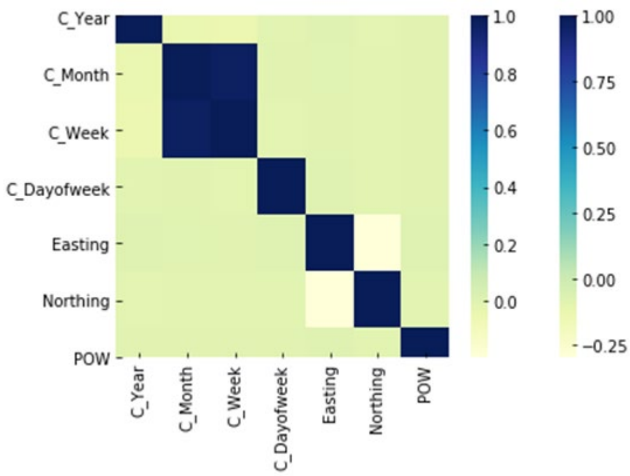

Figure 39 Correlational heat map for ML features

POW is an indicator determining whether the crime was within 20m of the Place of Worship or not. Easting and Northing are the coordinates of the crime.

In addition, three different dependent variables were included in the model building: offence category, Home Office code, and a combination of Home Office

[86] From those available from Kent Police crime data and Historic England location data. In future we would wish to experiment with incorporating other forms of data e.g. maximum air temperature on a given day.

code and sub- code. There were ten offence categories utilised for the model included ‘theft other’ offences, ‘criminal damage’ offences and ‘theft from motor vehicle’.

There were 55 Home Office codes used, and 152 Home Office sub codes. The classifiers performed relatively poorly for the Home Office and Home Office sub codes, so the following analysis omits these and focuses only on the offence categories as y values.

The machine learning was performed using Python 3.6 and its machine learning module scikit-learn.

The classifiers used were all based on decision trees, as these work well in this type of classification task.

Decision Trees handle classification problems by breaking them down into a series of decisions. The first decision is performed at the root of the tree; after this there are a series of branches, at each of which another decision is made, eventually leading to the final classification at the tree’s leaf.

A Decision Tree is designed to classify an object into one of two or more classes by asking a series of questions concerning the object’s attributes. In an ‘optimal’ decision tree at each stage the question asked must be one that provides the most information, which is determined by measuring entropy, the decision with the highest entropy should be asked closest to the root (Marsland, 2015).

The classifiers were Scikit-Learn's DecisionTreeClassifier, RandomForestClassifier and ExtraTreesClassifier. DecisionTreeClassifier implements a single decision tree, whereas the other two classifiers implement an ensemble of decision trees. Both the decision tree ensembles randomly select features in order to build multiple decision trees which are then averaged to produce a final result, by 'voting' for the classification outcome. RandomForestClassifier samples features with replacement, ExtraTreesClassifier samples features without replacement. RandomForestClassifier chooses questions based on the most entropy, whereas ExtraTreesClassifier chooses questions randomly (Geurts, 2006).

Other classifiers including XGBoost and neural networks were experimented with, but all provided worse performance outcomes than the tree classifiers.

Machine learning can suffer from either, or both of the problems of underfitting and overfitting. Underfitting means it does a poor effort in modelling the relationship between y and X. To counter this one method is to add more features, which often results in a better modelling of the relationship for the dataset. However, the drawback of this is that it will likely over fit the dataset, that is it models that dataset very well but will generalise poorly to other datasets.

For this data, the number of features is unlikely to be an issue, since there are not many, so to avoid overfitting a method called cross validation is used. Cross validation fits a model to the data repeatedly using samples of the data. Each fit is known as a fold and for this each classifier was run using grid search cross validation with five folds.

The performance of classifiers also can be determined by their hyper parameters, and during the cross validation, different hyper parameters were input into the grid search which produced the best performing model. Hyper parameters were chosen for the grid search as follows:

DecisionTreeClassifier 'criterion':['gini','entropy'],'max_depth':[4,5,6,7,20,90,150].
RandomForestClassifier 'criterion': ['gini', 'entropy'], 'n_estimators': [8, 16].
ExtraTreesClassifier 'n_estimators': [16, 32].

A description of these hyper parameters is beyond the scope of this report, suffice to say that these allow for a more thorough use of each classifier.

Table 20 below summarises the main features of the CWACHS PoW ML model.

Data sets	Crime in Kent over a 60-month consecutive period (1,122,180 entries)
Training set	70% of data set
Testing set	30% of data set
Method	Python 3.6 and its machine learning module scikit-learn. Decision Tree classification.
Decision tree classifiers tested	DecisionTreeClassifier RandomForestClassifier ExtraTreesClassifier
Variables (features) included	Year, Month, Week, Day of week, PoW, Easting and Northing, offence category
What to learn	Crime type, given that a crime has occurred within 20m of a Place of Worship

Table 20 Principal features of derived ML model.

10.4 Results of ML

In order to test the model, the data was divided into separate training and test data sets; using a ratio of 70% training to 30% test. The model was then fitted to the training data and the goodness of fit assessed against the test data.

To evaluate the classifiers, three metrics were used: accuracy, precision, and recall. Accuracy measures the proportion of classes that were predicted correctly, and for each of the classifiers used in this research over 90% were predicted correctly. This is a good performance for a classifier, but accuracy alone should not be relied upon to determine the efficacy of the machine learning employed. One reason for this is that because if, for example, 99% of the classes were all for a particular category, then simply classifying everything as that category would give you accuracy of 99%.

To complement this, other measures are used: precision and recall. Precision is the ratio of true positives to (true positives plus false positives) or, in other words, how good the classifier is at not labelling negatives as positives.

Recall is the ratio of true positives to (true positives plus false negatives), i.e. the ability of the classifier to identify positives. As can be seen from table 24 below, both precision and recall are close to 0.9 for each classifier, again indicating decent performance.

	Accuracy	**Precision**	**Recall**
DecisionTreeClassifier	0.90543797	0.88304767	0.87915129
RandomForestClassifier	0.90814452	0.90895658	0.87705049
ExtraTreesClassifier	0.90600521	0.90049216	0.87647613

Table 21 Measures of accuracy, precision and recall for the ML model.

10.4.1 Example of ML prediction of PoW heritage crime

So given a crime's location, whether it is within 20m of a place of worship and its date, machine learning can make a good ‘guess’ at the offence category and be also able to make reasonably good predictions about crime categories based on temporal and geographical features.

For example, RandomForestClassifier was used to determine crime category (since it performed best in two of the three metrics) for a crime with Easting 123456[87], Northing 987654[88], within 20m of POW = yes, date= 03/01/2015, then the model predicted likeliest Offence Category to be 'THEFT OTHER OFFENCES' with probability 0.875. The actual category was indeed 'THEFT OTHER OFFENCES'.

[87] Not actual coordinate.
[88] As above.

11 Conclusions and recommendations

In this section of the report we collect together the most significant of the results of our research, in a conclusions subsection. This is followed by a discussion of the approach currently adopted to prevent heritage crime and how this might be improved. We then look at the potential for developing a 'heritage crime risk index', based on current practice in cognate areas of crime prevention. The report concludes with a list of recommendations.

11.1 Conclusions of research

Our research was concerned with the geographical areas of Kent and Medway and involved the spatial and temporal analysis of 'heritage-specific offences', 'targeted heritage crime' and 'crime within, at or close to heritage sites'. We termed the latter 'CWACHS' for the purposes of this report.

We also looked in more detail (at the request of Historic England) at the three existing Heritage Action Zones (HAZs) in Kent and Medway.

The period under study was 01/01/2014 to 31/10/2018 inclusive.

The crime data consisted of offence type and location details for the 1,122,180 crimes recorded by Kent Police during the period under study.

The geographical data we utilised included locations of Conservation Areas, Listed Buildings, Scheduled Monuments, Registered Parks and Gardens, Registered Battlefields, World Heritage Sites, Protected Wreck Sites and 'Heritage at Risk' sites in Kent and Medway.

In terms of our findings, it is currently not possible to report with any reliability on the frequency of heritage-specific crimes in Kent and Medway. We note elsewhere in this report the difficulty of identifying specific heritage crimes within the current police database, which suggests the need for a different approach to their recording.

During the period of study there were a total of 96,013 recorded CWACHS, spanning 153 crime types, of which 106 recorded at least one crime during the period. On average, approximately 9% of all recorded crime in Kent and Medway occurs within, at, or close to, a heritage site. The mean number of CWACHS in Kent and Medway is approximately 19,844 offences per year, or 54 offences per day. However, most of these offences would not have been targeted heritage crimes.

The cyclical variation according to time of day of CWACHS appears to follow the same as that of 'all crime': a minimum at around 7am, rising relatively quickly until about 2pm, constant thereafter until about midnight and then declining steeply. However, one noticeable difference between CWACHS and other crimes (particularly in recent years) is a marked 'spike' in offending at around 6am. This remains unexplained.

Our best estimates suggest that currently approximately one in five Listed Buildings and one in four Places of Worship in Kent and Medway experience some form of crime each year. About one in ten Scheduled Monuments suffer crime, or it occurs nearby. Just over one half of Registered Parks or Gardens have one or more crimes a year within them. For Conservation Areas the proportion is (not unexpectedly) much larger, at closer to four in five.

The 'top three' offence types within CWACHS are 'theft offences', 'criminal damage' and 'burglary non-dwelling' and these constitute for just over half the total number (56.2%), with the remaining 150 offence types distributed between just under one half (43.8%).

CWACHS at Places of Worship, Scheduled Monuments and Conservation Areas follow the same rank order (in decreasing frequency): 'theft offences', 'criminal damage', 'burglary (non-dwelling)', 'public order offences' and 'burglary (dwelling). However, although the rank orders for these types of heritage location are 'roughly' the same, the distribution of frequencies within crime categories differ significantly.

Registered Parks and Gardens have a different rank order with (in decreasing frequency) 'theft offences', burglary (non-dwelling)', 'criminal damage', public order offences' and 'burglary (dwelling)'.

The subset of CWACHS which are 'targeted heritage crimes' were assessed using a random sampling technique. This suggested that between 2% and 12% of crimes were targeted heritage crimes, although due to sample size this estimate should be treated with caution.

The numbers of CWACHS in Kent and Medway were decreasing until about late Summer/early Autumn of 2015 and thereafter began to rise. However, the rate of increase in numbers of CWACHS was comparable to that of most other types of crime in Kent and Medway.

The number of 'public order offences' at CWACHS grew as a proportion of the total over the period under study, and this in part explains some of the overall increase since 2015.

By applying a chi-squared test to LSOA-level data for CWACHS and non-CWACHS, we established that CWACHS numbers are higher than expected in rural villages, hamlets and near isolated dwellings than can be attributed to chance. However, this was not the case for rural towns and fringes.

We also utilised local Moran's I to identify spatial clusters at a regional level using LSOA-level crime data. This revealed several LSOAs on the fringes of areas of high levels of crime that could be particularly vulnerable to the spread of crime and therefore heritage-specific locations within these areas could be managed to halt the 'spread' of crime towards the periphery of the town.

Allocating crimes to different categories of urbanization and rurality reveals that the distribution of CWACHS incidents is significantly lower than expected in major urban areas (specifically the Gravesend-Dartford area), while increasingly greater as rurality increases. This implies that initiatives to protect heritage sites in remote locations would produce positive results.

The three HAZs have very different characters, and this is reflected in their respective levels of crime, and the frequency of each type of crime. The differences in CWACHS crime is even more distinct, exaggerated by the relative sparseness of these sites in Swanscombe and Greenhithe.

The physical characteristics of the three locations also affect the distribution of crime. Leeds and Hollingbourne is a large rural expanse with dispersed crime, the Ramsgate Zone covers the town centre with few crime-free areas, while Swanscombe and Greenhithe is divided by quarries and other areas that are not accessible to the public, resulting in very clustered patterns. This emphasises how the environment can shape the patterns of crime.

A further factor influencing the spatial pattern of crime within each HAZ is the morphology (shape) of the area, which may be strongly determined by physical barriers such as the coastline or riverside as well as internal features such as quarries or reservoirs. Since accessibility by road generally governs all activity associated with heritage-specific locations, including crime, it is important that routes to and from these locations – as well as in and out of the vicinity – are considered in any future strategy.

In Kent and Medway Places of Worship (mostly Christian churches) are experiencing increasing numbers of crimes, and this has been particularly the case since around summer 2016. The rate of increase appears higher than that of all other crimes in the same period, both in general and at other heritage locations.

There is clear statistical evidence that metal thefts from churches have also been increasing markedly since around summer 2016. The rate of increase appears higher than that of most other crimes. There is statistically significant correlation between metal thefts from churches in Kent and Medway with both the price of lead and mixed brass.

Finally, we discovered that machine learning as a method of heritage crime prevention shows promise. We conducted an initial analysis aimed at predicting crime categories (with some success), but it is envisaged that 'richer' crime report data would allow for more complex relationships to be investigated, and machine learning based software to be developed that would predict temporal aspects of crime based on their profiles (a profile being various attributes of the crime, that would be extracted from its crime report along with similar features used within the current analysis). In this way a risk assessment tool could be constructed for use by Historic England.

11.2 Preventing heritage crime in Kent and Medway

One of the objectives of this research was to achieve a greater understanding of heritage crime in Kent and Medway, with potential implications for other places in England. The results of this project could potentially inform Historic England's heritage crime prevention strategies.

Currently Historic England promotes situational crime prevention strategies, that is strategies which 'Increase the effort', 'Increase the Risks', 'Reduce the Rewards', 'Reduce Provocations' and 'Remove Excuses' (Historic England, 2018a, p.4) within the context of 'twenty five techniques of crime prevention' (Historic England, 2018b).

As Yates and Mackenzie (2018, p. 204) note, situational crime prevention 'looks to "target hardening": changes to the physical environment that can protect objects, sites, and areas against crime'.

Routine-activity theory ('RAT', first described in Felson, 2002) is one of the most well-known and cited theories in environmental criminology and is predicated upon an understanding of the relationship between an individual's everyday experiences and his/her criminal behaviour. It defines criminal opportunities in terms of three interrelated and necessary components: a motivated offender; a suitable target; and the absence of a guardian. The thesis is that criminal opportunities arise when these three components coincide. For example, in a certain situation the number of offences might increase if there are few guardians and plenty of suitable targets, even if there is no increase in the number of motivated offenders. Intuitively, routine activity theory is well-understood and aspects often feature in the crime prevention literature.

For example, the Ecclesiastical Insurance Group advises those responsible for church buildings to 'maximise surveillance levels, including cutting back tall trees and vegetation which could otherwise provide a screen to hide criminal activities' (Ecclesiastical Insurance Group, 2017, p.2); a clear reference to increasing the guardianship of the churches concerned. Similarly, as Andy Bliss argued, '[t]he vast majority of crimes committed against the historic environment are not intricately planned offences committed by organised criminal gangs – they are committed by individuals or small groups following the path of least resistance to easy cash' (ACPO, 2013, p.3).

Our research shows that adopting an RCT and RAT based approach to countering targeted heritage crimes is a largely sound one. For example, criminal damage hotspots that effect heritage locations often correspond with more general measures of vulnerability such as low-surveillance locations, the existence of a night-time economy. The guardianship and protection offered to locations such as Canterbury Cathedral seem effective deterrents to many of the forms of crime we found associated with heritage locations in our research.

Thus, whilst there may be some basis to Poyser and Poyser's (2017) claim that 'traditional methods of policing and crime prevention are ordinarily made redundant in the face of heritage assets and sites' (p.247) it may be a case of a more tailored approach, reflecting the different forms of vulnerability (type of heritage site, location, time and so on) rather than a complete change to the current approach.

For example, proactive crime prevention, utilising the current Historic England approach could be conducted in geographical areas containing heritage crime locations that fall within an area with a high Moran's HL index (see 6.2.1) at times of year when Places of Worship are most at risk.

One area of heritage crime prevention that appears to us to be under-researched is that of 'repeat victimisation'. It is important to note that 'victimisation' in the academic literature (and to a lesser extent in policing circles) applies to more than people: it can include crime 'against' listed buildings and scheduled monuments[89].

An important distinction is between 'pure repeat' victims and 'near repeat' victims. Pure repeats are when the same 'target', for example the same church is repeatedly victimised (for example, repeated theft of the lead from the roof). Near repeats on the other hand are (for example) when one listed building in a conservation area has been subject to criminal damage through spraying a 'tag', and then nearby listed buildings are damaged soon after. The distinction is important as the two types of victimisation are thought to occur for somewhat different reasons (see Chainey, 2012).

The reasons for pure repeat victimisation are not clearly understood, although research does suggest a number of possible factors (including combinations of factors). For example, the same listed building may be repeatedly burgled (sometimes by the same offender or offenders) and the reasons for this could be that:

- there is something inherently 'risky' about the location of the listed building itself (it is close, but not too close to an offender's 'anchor point' – see Routine Activities Theory);
- the perpetrator will be familiar with the layout of the building;
- the perpetrator will be aware that stolen items may have been replaced with new ones.

'Near repeat victimization' is one possible contributing factor to the existence of geographically located crime hotspots (see section 3.2). It is sometimes claimed that, 'primarily high crime areas are high because of numbers of repeat victimisation' (Pease, 2018). The modelling of near repeat victimisation is often built into the algorithms for so-called 'predictive policing'. This might also prove to be the case when building machine learning algorithms for predicting heritage crime.

Repeat victimisation is also one of the features of the 'HOPPER' approach to risk assessing archaeological sites at risk of acquisitive crime proposed by Grove, Daubney and Booth (Grove et al' 2018) with the longer term aim of using a Red Amber Green (RAG) rating 'to target crime prevention and policing resources appropriately' (ibid, p.1042).

11.3 Developing a heritage crime risk index

In 2012 Cheshire Constabulary introduced a 'Heritage Sites Risk Assessment Tool', which uses a points system where risk factors and prevention measures are allocated a score (a points system, which appears to be in multiples of five, ranging

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[89] Perhaps it would be better to use the word 'target' rather than 'victim', but this is not common.

from 5 to 40[90]). A total risk score for a heritage location is arrived at by adding the points for risk factors but subtracting those for prevention measures. For example, if the answer to the question 'Is the?' a 'Yes' then this attracts a score of 40. is counted as a risk factor of 10.

There are a number of obvious advantages in using risk assessment tools, not least of which is the simplicity and clarity of the risk assessment process and outcome. It is also commendable of Cheshire Constabulary to attempt to put risk assessment of heritage sites on a more scientific basis.

However, there are significant problems with the use of numerical scales for assessing risk factors and combining them in the way that appears to be recommended. One unavoidable technical problem is that when we quantify risk in a simple numerical manner using integers (whole numbers) we are treating nominal variables as if they were scale. Put another way, how appropriate is it to consider that 'a heritage asset being unoccupied for more than a day (a score of 40) carries four times the risk of 'ladders being stored in open or easily accessible areas' (a score of 10)? This may be the case and further statistical research would help in establishing this.

As far as we are aware, no rationale (statistical or otherwise) has been offered concerning why a linear scale has been used rather than, say a logarithmic one. The problem is further confounded by the adding and subtracting of risk scores, which is presumably based upon an assumption that the risk factors are independent of each other (otherwise a conditional Bayesian probability would be more appropriate).

Again, these questions could be addressed through access to higher quality data on heritage crime.

Finally, in 2018 Historic England introduced a 'Heritage Crime Risk: Quick Assessment Tool', Step 2 of which uses red shading to indicate higher risk within a '9 by 6' table (Historic England, 2018a, p.2). The table consists of nine risk factors and six heritage assets. Three of the six heritage assets correspond in the main to those studied as part of this research. Many of the nine risk factors (such as 'Does the asset have accessible external metal? (lead, copper)') seem appropriately based on existing crime prevention theory (particularly Routine Activities Theory), practice and are evidence-based.

However, some of the other risk factors listed (such as 'Is the local crime rate high?') might benefit from an assessment against the available data and be made more specific and contextualised.

[90] We were unable to locate details of the scoring system.

11.4 Recommendations

As a result of our research for this report we make the following recommendations to Historic England.

1. Our research into crime at, or from, Places of Worship suggests the continued existence of 'unregulated disposal routes' (APPG, 2018, p.2) in Kent and Medway for scrap metal thefts. In the SE of England these could also possibly include Nord - Pas de Calais, southern Belgium and northern Picardy [91]. Further research on the reasons for the continuing growth in metal theft from churches is urgently needed[92].
2. Consider commissioning research in a geographical area where the local police service(s) have been 'flagging' heritage crime. If this is not possible consider instead funding a larger random sample of crimes within, at or close to heritage locations.
3. In the event of a lack of a national adoption of heritage crime 'flagging' on the NCRS consider working with higher education and police analysts to devise natural language processing could automatically flag potential heritage crimes. This could include a series of key terms, e.g. 'treasure', 'monument', 'church', 'metal theft' and 'metal detecting' that are used in the incident descriptions.
4. Develop a more detailed definition of 'heritage crime', with both inclusion and exclusion criteria. We consider that in some ways the 2013 ACPO definition ACPO, 2013, p.12) was more helpful.
5. Test and develop existing heritage crime risk assessment methods and assess the evidence base for those that have been proposed (e.g. 'HOPPER' and the red/green/amber system for risk identification of heritage sites as per Grove et al., 2018).
6. Develop machine learning algorithms that would predict temporal aspects of heritage crime based on their profiles. This would require a richer data set e.g. sanitised crime reports.
7. Consider a further project that analyses of repeat victimisation rates for targeted heritage crime, particularly in terms of listed buildings and Places of Worship (e.g. to test whether they exhibit distance-decay patterns).
8. In general terms, more research is needed (in which data would form a part) into the use of intelligence to identify serious heritage crime offenders (e.g. are there 'self -selecting' opportunities? Is there 'comorbidity' where certain forms of heritage crime coincidence with other crimes, such as wildlife offences?)
9. The analysis of crime types in this report could be used to target specific crime types, helping to reduce the opportunity for crime where it is most prevalent.

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[91] A search for 'ferrailleur', 'récupération ferraille' and similar terms showed 25 to 30 scrap metal dealers in Nord - Pas de Calais, southern Belgium and northern Picardy.

[92] This research might also include any impact of the UK's withdrawal from the EU and the end of the transition period on 1 January 2021.

10. Consider an initiative to improve surveillance at Listed Buildings/PoWs on the fringes of urban centres, since these appear to be more vulnerable than remote rural locations in attracting crime.

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Appendix A Density Maps

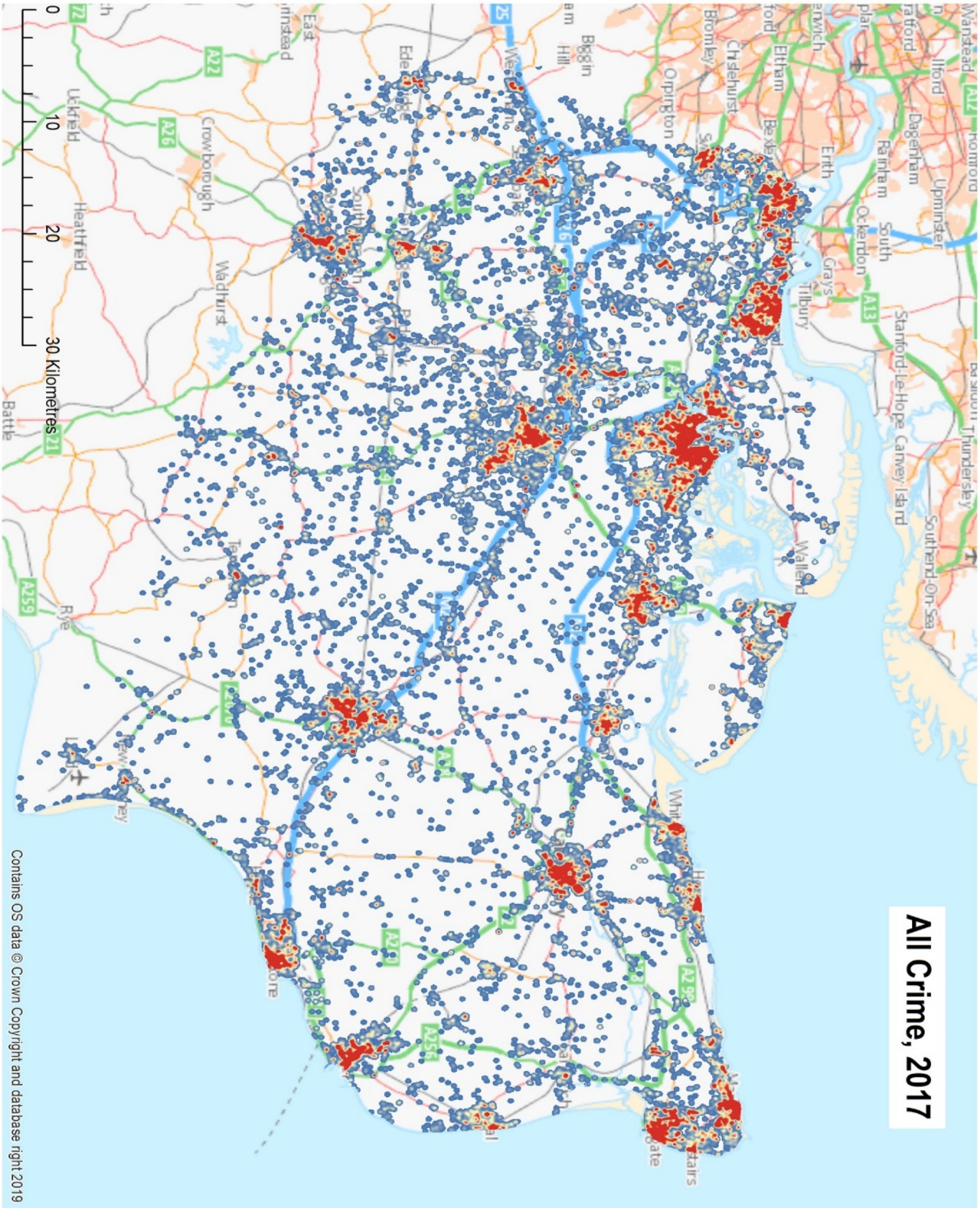

Figure A1 Density map for all crime in Kent and Medway, 2017

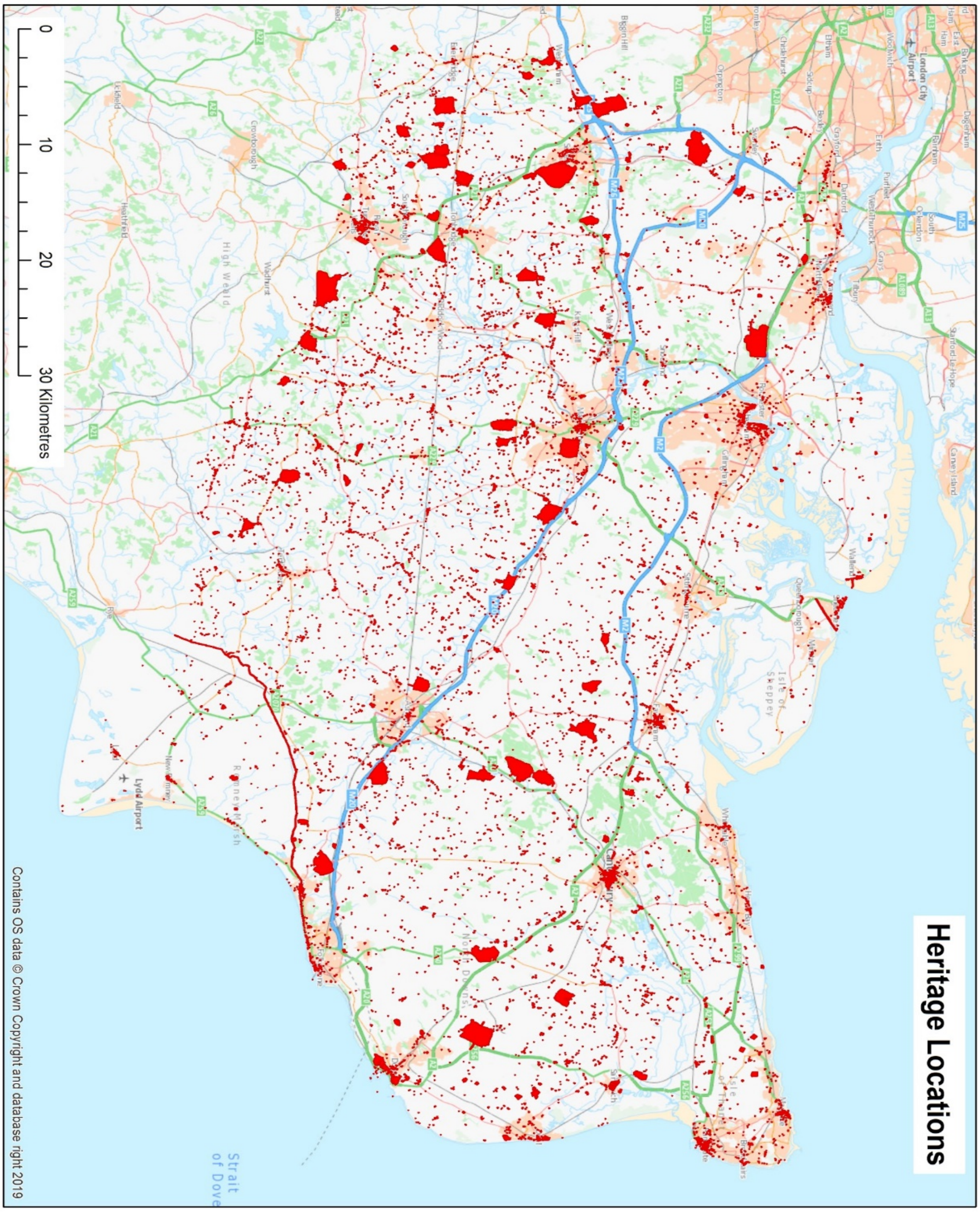

Figure A2 Heritage locations in Kent and Medway (as of 2019).

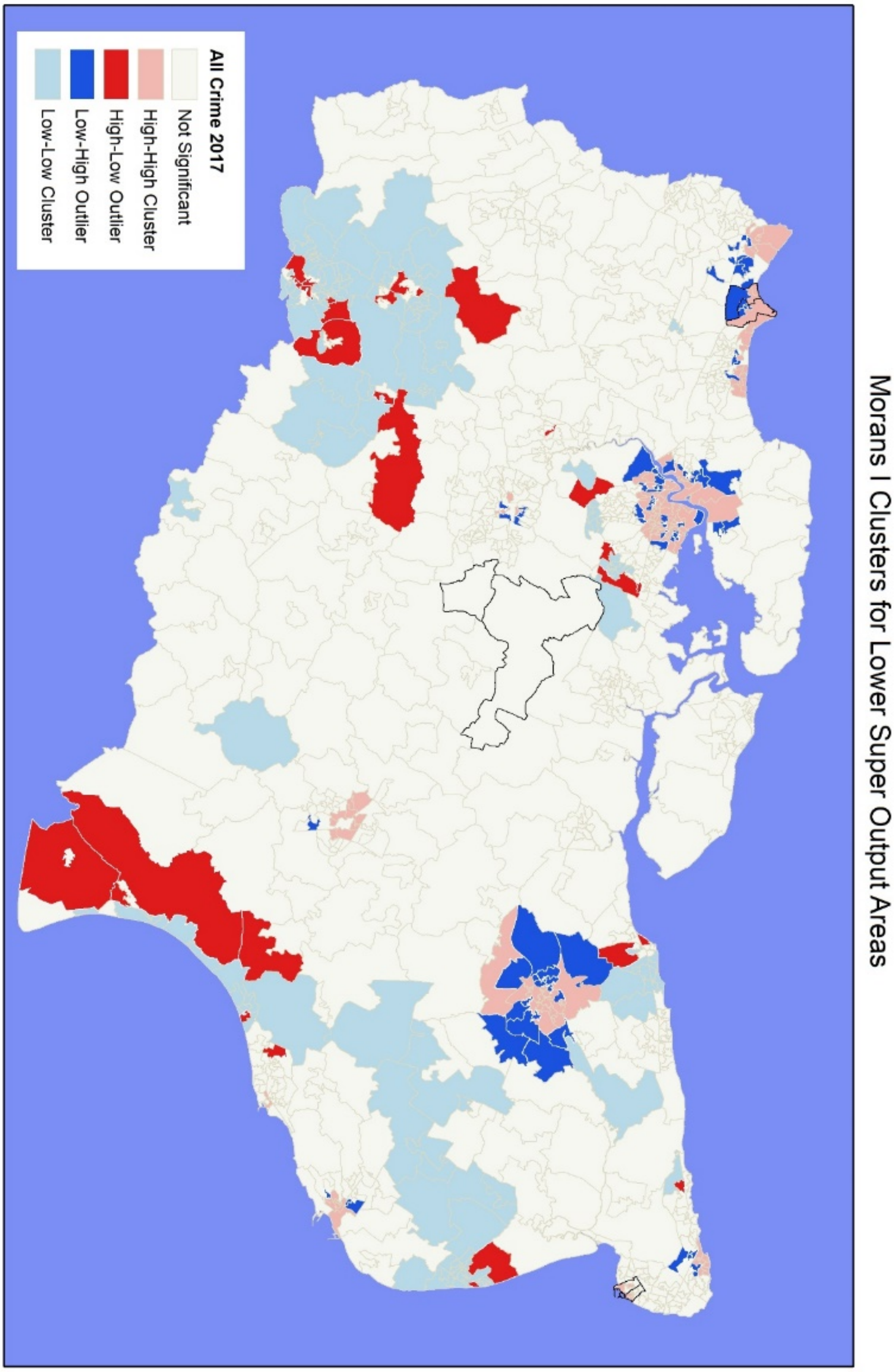

Figure A3 Local Moran’s I clustering, Kent and Medway, 2017

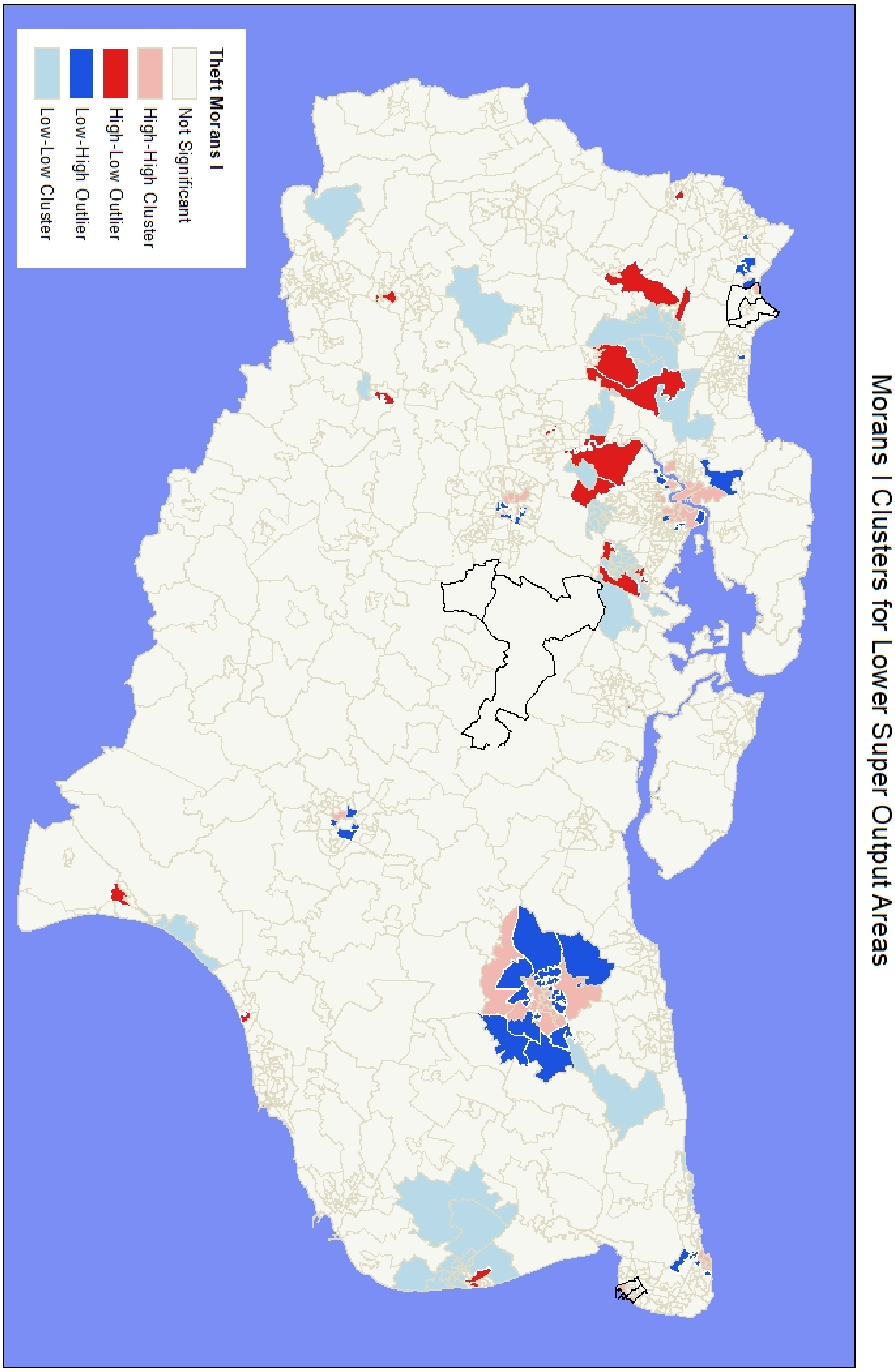

Figure A4 Local Moran’s I clustering for theft, LSOAs, Kent and Medway.

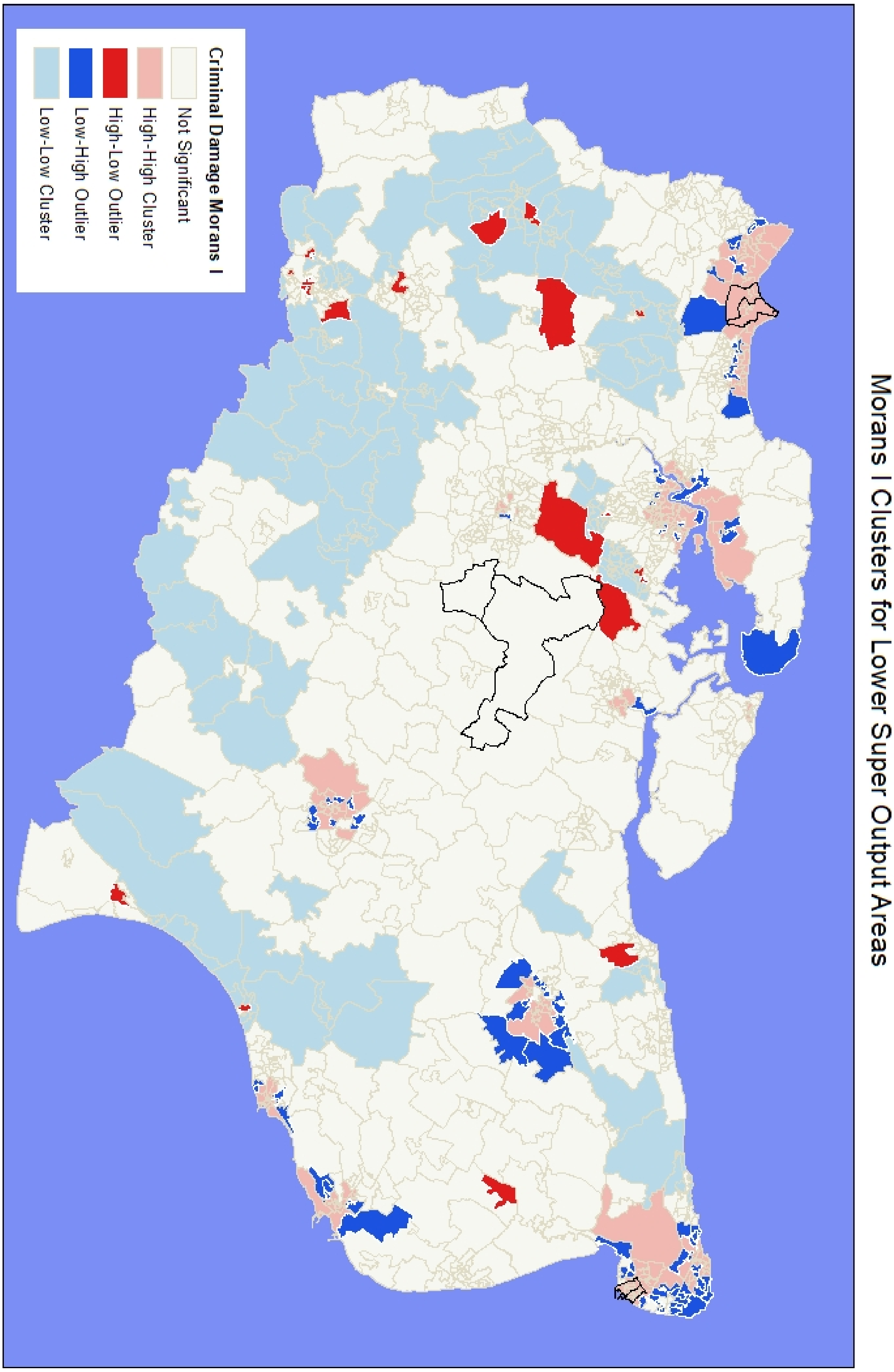

Figure A5 Local Moran's I clustering for criminal damage, LSOAs, Kent and Medway.

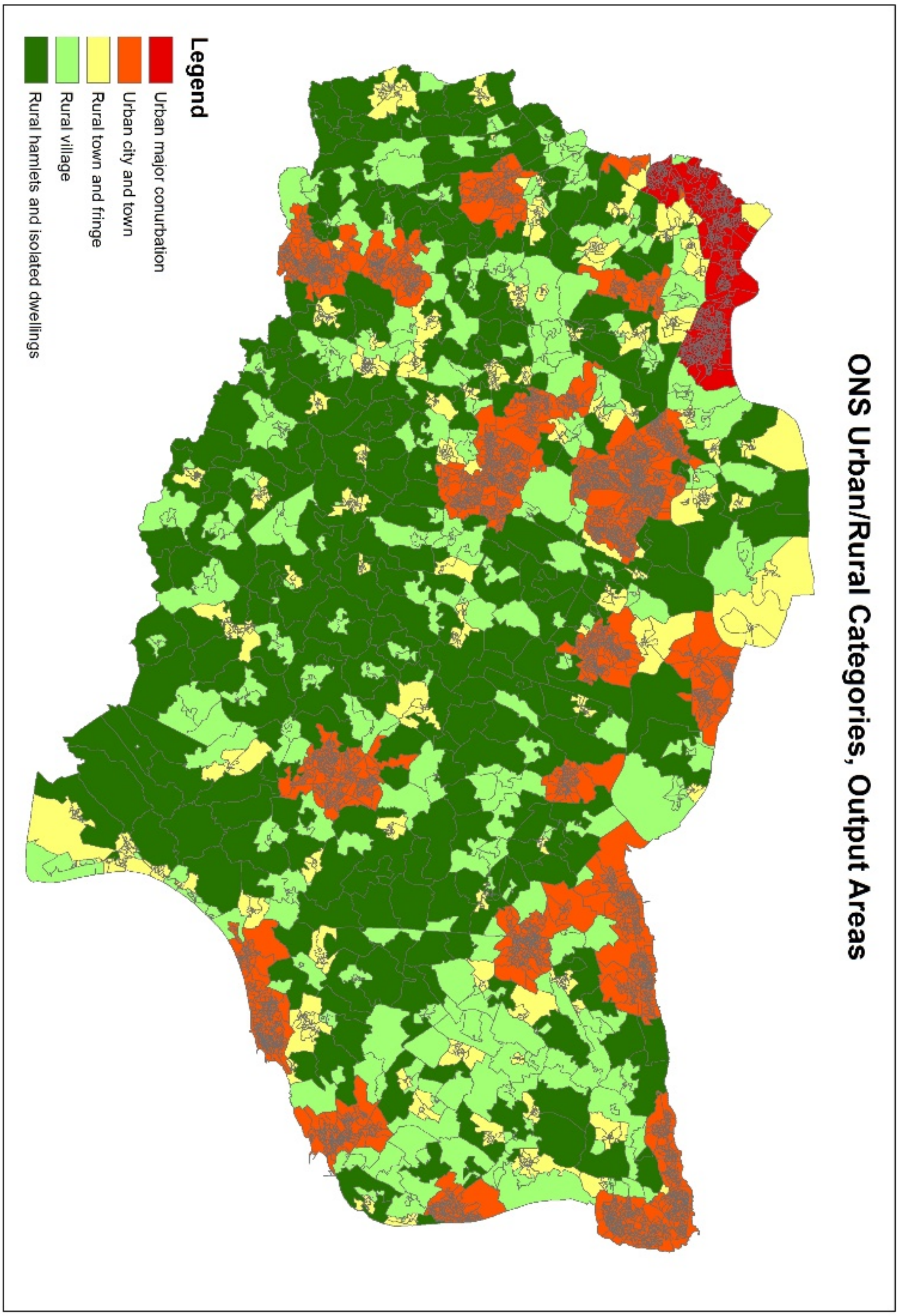

Figure A6 ONS Urban/Rural areas, Kent and Medway.

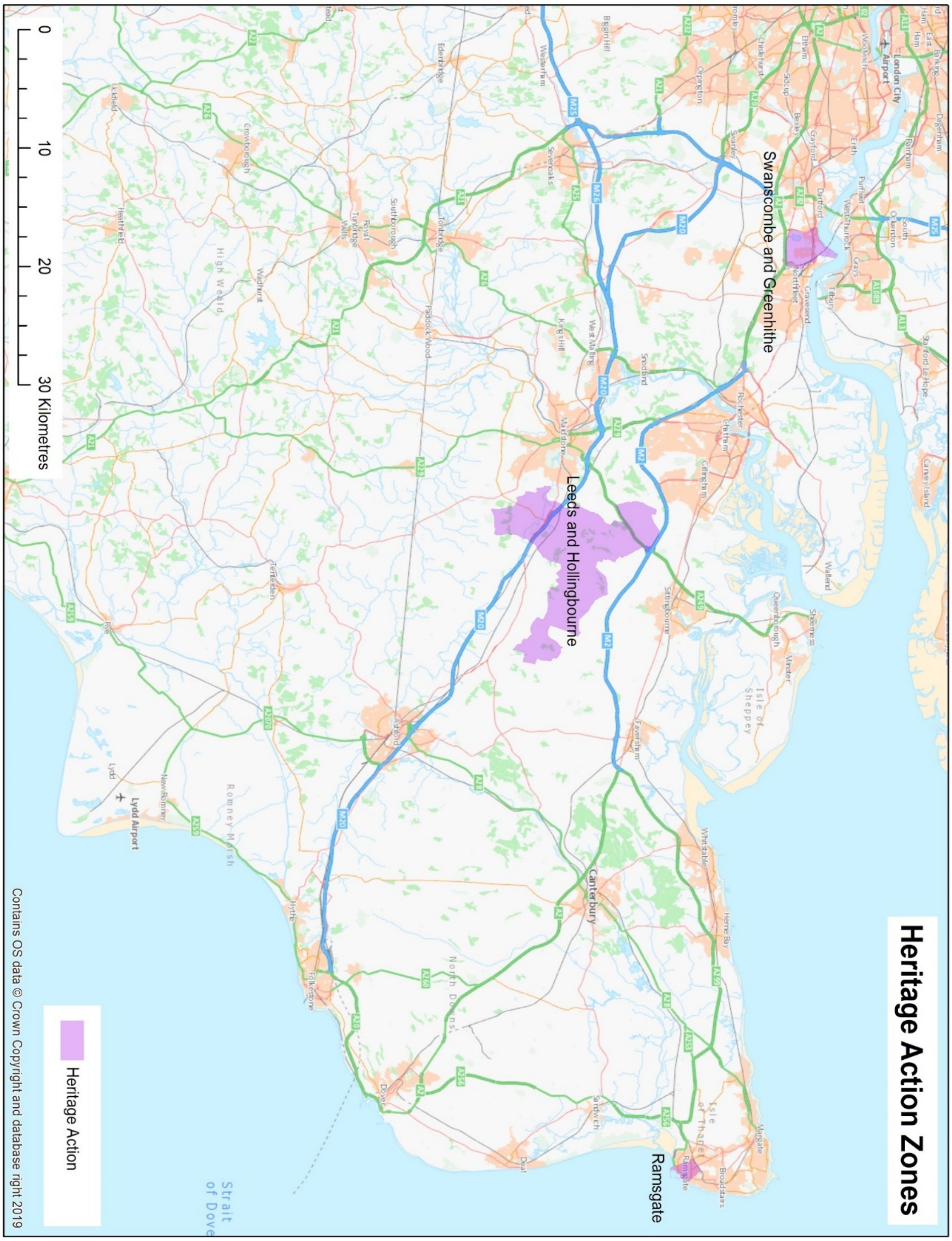

Figure A7 The three HAZs included in the study.

Appendix B Tables

Month and Year	Frequency
Jan-14	221
Feb-14	173
Mar-14	165
Apr-14	244
May-14	218
Jun-14	314
Jul-14	172
Aug-14	185
Sep-14	274
Oct-14	209
Nov-14	167
Dec-14	212
Jan-15	182
Feb-15	196
Mar-15	180
Apr-15	171
May-15	203
Jun-15	270
Jul-15	206
Aug-15	210
Sep-15	224
Oct-15	204
Nov-15	298
Dec-15	198
Jan-16	228
Feb-16	142
Mar-16	182
Apr-16	161
May-16	174
Jun-16	166
Jul-16	189
Aug-16	204
Sep-16	233
Oct-16	212
Nov-16	214
Dec-16	232
Jan-17	219
Feb-17	203
Mar-17	176
Apr-17	231
May-17	241
Jun-17	210
Jul-17	223
Aug-17	264
Sep-17	213
Oct-17	272
Nov-17	220
Dec-17	243
Jan-18	220
Feb-18	151
Mar-18	309
Apr-18	240
May-18	361
Jun-18	312
Jul-18	213
Aug-18	364
Sep-18	262
Oct-18	268
TOTAL	**12848**

Table B1 Monthly numbers of crimes at or near PoWs, Kent and Medway.

Month/Year	Number
Jan-14	1
Feb-14	4
Mar-14	2
Apr-14	0
May-14	2
Jun-14	1
Jul-14	0
Aug-14	5
Sep-14	2
Oct-14	0
Nov-14	0
Dec-14	2
Jan-15	1
Feb-15	1
Mar-15	0
Apr-15	0
May-15	0
Jun-15	2
Jul-15	1
Aug-15	4
Sep-15	4
Oct-15	2
Nov-15	3
Dec-15	1
Jan-16	0
Feb-16	0
Mar-16	1
Apr-16	1
May-16	0
Jun-16	0
Jul-16	0
Aug-16	3
Sep-16	2
Oct-16	5
Nov-16	2
Dec-16	2
Jan-17	0
Feb-17	1
Mar-17	3
Apr-17	4
May-17	1
Jun-17	2
Jul-17	1

Aug-17	1
Sep-17	7
Oct-17	5
Nov-17	0
Dec-17	2
Jan-18	3
Feb-18	1
Mar-18	4
Apr-18	4
May-18	0
Jun-18	1
Jul-18	1
Aug-18	6
Sep-18	1
Oct-18	3
TOTAL	**105**

Table B2 Monthly totals of metal thefts from PoWs, Kent and Medway.

	Lead Price £/Tonne	Mixed Brass £/Tonne
Jan 2014	950	2100
Feb 2014	900	2100
Mar 2014	950	2000
Apr 2014	900	1900
May 2014	950	1950
Jun 2014	950	2150
Jul 2014	950	2100
Aug 2014	950	2100
Sep 2014	950	2100
Oct 2014	900	2000
Nov 2014	950	2000
Dec 2014	950	2000
Jan 2015	900	1900
Feb 2015	900	1900
Mar 2015	850	1900
Apr 2015	850	1900
May 2015	900	1900
Jun 2015	900	1900
Jul 2015	850	1800
Aug 2015	800	1700
Sep 2015	800	1700
Oct 2015	800	1700
Nov 2015	850	1700
Dec 2015	750	1700
Jan 2016	750	1700
Feb 2016	800	1700
Mar 2016	850	1700
Apr 2016	900	1700
May 2016	900	1800
Jun 2016	900	1800
Jul 2016	950	1900
Aug 2016	1000	1900
Sep 2016	1000	1800
Oct 2016	1000	1800
Nov 2016	1100	2000
Dec 2016	1100	2000
Jan 2017	1150	2200
Feb 2017	1200	2200
Mar 2017	1200	2300
Apr 2017	1100	2200
May 2017	1100	2200
Jun 2017	1100	2200
Jul 2017	1100	2300
Aug 2017	1100	2400
Sep 2017	1150	2600
Oct 2017	1250	2500
Nov 2017	1400	2600
Dec 2017	1400	2600

Jan 2018	1400	2700
Feb 2018	1350	2700
Mar 2018	1400	2700
Apr 2018	1250	2700
May 2018	1250	2800
Jun 2018	1350	2900
Jul 2018	1300	2600
Aug 2018	1250	2600
Sep 2018	1200	2600
Oct 2018	1200	2700

Table B3 National monthly lead and mixed brass prices.