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Green and Blue Spaces and Health: A Health-led Approach

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Government of Ireland

ENVIRONMENTAL PROTECTION AGENCY

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DISCLAIMER

The EPA Research Programme addresses the need for research in Ireland to inform policymakers and other stakeholders on a range of questions in relation to environmental protection. These reports are intended as contributions to the necessary debate on the protection of the environment.

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Executive Summary

Project Description

- This research was based on a 12-month desk study that modelled, for identified sample sites, the relationships between health indicators and the availability of green and blue infrastructure (GBI).
- The value of the research was that it provided a route to identify measurable effects and results from a cross-sectional and area-based study.
- Multiple research shows that good-quality environments have detectable health benefits. Although the presence of/access to GBI has been shown to improve health outcomes, there is less evidence on the magnitude of the effect that GBI elements have on health.
- Previous research has been "GBI led", with study sites selected primarily based on where GBI data are available. This project used a "health-led" approach, identifying sites of interest based on existing health data, with subsequent characterisation of the GBI elements in these sites of interest.
- An audit of Irish health data identified specific health measures that were available at meaningful geographical scales. The audit enabled study site selection based on usable and comparable sets of health and associated GBI data for the same locations.
- Spatial modelling identified a range of findings across scales, which showed a mixed pattern of association between health outcomes and the amounts of GBI.
- Developing approaches using geographic information systems (GISs) and geospatial modelling techniques will add to the evidence base concerning the positive effects of green and blue spaces for human health and inform environmental and health and well-being policy nationally.

Literature Review

- A focused and small-scale scoping review was carried out of established academic research that included a more considered focus on blue space and water-based infrastructures. The review followed a "health-led" search path and identified a relatively small amount of literature using this approach.
- First, an assessment of the effects of overlapping GBIs provided better insight into the magnitude of derived health benefits.
- Second, the review noted the use of indirect and proxy health indicators to provide more robust information on the magnitude of health benefits of GBIs. Additional individual-level health data can augment the quality of self-reported health data. Finally, more fully developed longitudinal studies are needed to assess the long-term effects of GBI on human health.
- Third, enhanced access to publicly available, spatially referenced, high-resolution longitudinal health data are needed for rigorous multi-scale and longitudinal assessments at the GBI and human health research interface.
- Based on the literature the focus of the study was on a more nuanced understanding of place type, the use of multi-scalar geospatial data (measured, self-reported and proxy) and specific statistical modelling that incorporated different scales and time periods.

Data Audit and Site Selection

- The project's data audit was built in part on key recent data audits, both from 2014, by the Environmental Protection Agency (2014) and Health Information and Quality Authority (2014). These audits did not fully focus on whether the identified data sets were available at meaningful spatial scales, either individual or areal, nor the degree to which these data sets were accessible.
- Core health indicators came primarily from statutory sources. These included self-reported and derived health indicators from the Central Statistics Office, independently collected data on mortality (from Maynooth University) and additional data from surveys and administrative sources (e.g. Health Service Executive, Department of Health). A final criterion was the

selection of data that was mappable at a scale that could be overlaid with detailed GBI data.
- The final list of usable data sets included those formortality, self-reported health, disability and deprivation (a proxy and mediating factor for health outcomes). These data were available and aggregatable from small areas to higher levels, including a new intermediate area geography.
- Case study selection was based on three procedures: cluster analysis, data matching and expert consultation. Cluster analysis was carried out within a GIS and used to identify spatial clusters of good and bad health at multiple scales that included spatial outliers.
- Cluster analysis was carried out at five scales (county level, intermediate area level, settlement level, electoral district level and small area level). Data from different time points were considered within the clustering procedure as follows: mortality (2006, 2011), self-reported health/ disability (2011, 2016) and deprivation (2006, 2011 and 2016).
- Using data matching, a first set of case study/ sample sites was identified, showing clusters of "good" health (low mortality rates, good self-reported health, low rates of disability and deprivation) over the selected time periods. A second parallel set of case study/sample sites was identified from clusters of "bad" health (high mortality, poor self-reported health, high disability rates and deprivation scores) for the same time periods.
- These two steps produced an indicative list of sample sites, 63 in total, for multi-scale modelling for county, intermediate area and settlement levels. A further selection of 10 case study sites for single-scale modelling at the intermediate area level was based on consultations between specific stakeholders, including the study's policy partner (Eastern and Midlands Regional Assembly), the funding body and sister projects (Environmental Protection Agency).

GBI Characterisation

- A survey of available GBI data sets focused on data matching with the chosen study sites. A number of data sets were assessed, including CORINE, Urban Atlas and additional satellite data sets.
- Constraints included full geographical coverage for study sites, identifiable and available classifications of GBI, affordability and a minimum level of pre-processing required.
- The GBI data sets selected were CORINE (for multi-scale modelling) and Urban Atlas (for single-scale modelling), as acceptable compromises between resolution, geographical coverage and GBI classifications.

Statistical Results

- The statistical results confirmed associations of good health outcomes with the presence of GBI and associations of poor health outcomes with lower levels of GBI.
- The statistical modelling separated out green and blue indicators and found stronger associations with green than with blue space.
- There were some inconsistent and reverse associations, especially between some of the specific health indicators and the presence of GBI, particularly in relation to mortality data.
- Regression (R^2) scores were stronger at the intermediate area level than at county and settlement levels, confirming its potential as a sound scale for reporting data.

Summary and Recommendations

- The study identified, even with data limitations, that it is possible to begin to clarify a magnitude of effect, based on a statistical association, between health and GBI data sets. These associations were mapped at several spatial scales of aggregation and a multi-scalar approach is an innovation of this work.
- The study drew from key spatial modelling tools within a GIS to aggregate and match data, to identify clusters of health outcomes not available through other means, and used the GIS as a tool to extract data that could be used in the statistical modelling.
- Longer term studies in which more time is spent on data identification, mining and standardisation will deepen the initial analyses reported here. This applies especially to extending the range and type of health indicator, with potential examples identified around prescribing, hospital utilisation and longitudinal data. Similarly, new

European Union satellite data from the Copernicus programme open up the potential for much finer-level analyses that could greatly enhance the ability to build detailed GBI characterisation into future work.

- A key overall recommendation is the urgent need for a new and accessible "intermediate" level of geography for the collection and reporting of health data in Ireland. This may be a combination of existing service-level units or a new set of boundaries such as the intermediate areas identified in this project. This should form the basis of discussions across many of the policy sectors within which Healthy Ireland operates, as a means to better "mine" health data with a spatial component.
- Another potential tool for opening up future health data work is the new individual-level postcode, Eircode. Although some years away from full integration, the design of an anonymised spatial tag has already created a valuable technical tool for both individual and areal-level health data modelling.
- As part of a wider discussion on the availability of and protocols for access to good-quality detailed health data, we also draw attention to the recent DASSL report by the Health Research Board, although again we would suggest a more visible role for geospatial detail in those discussions.

1 Introduction

1.1 Overview

A large body of evidence exists showing that the provision of, and access to, a good-quality environment has detectable health benefits. These benefits include, *inter alia,* reduced stress and stress-related illness, increased physical activity and higher self-reported satisfaction. However, although the presence of green and blue infrastructure (GBI) has been shown to improve health outcomes, consensus is lacking in the literature as to the magnitude of effect that GBI elements, such as parks and street trees, have on the health of populations. Additionally, most research in this area appears to be "GBI led", that is, studies are performed where GBI data are available. This research examined the GBI/health interaction from a "health-led" direction, that is, sites of interest were chosen based on existing health data, with subsequent characterisation of the GBI elements in these sites of interest. Drawing on international research and best practice, this study informs discussions around the environment/health interactions by identifying areas of high and low reported health and then characterising the GBI elements of these areas, thereby identifying the elements and configurations of elements contributing to these health outcomes.

1.2 Rationale

The concept of ecosystem services, the goods and functions provided by the environment and the values of such functions, has become well established (Hein *et al*., 2006). Beyond the obvious goods provided by well-functioning environmental systems, such as food and clean water, less obvious functions are provided in the form of pollutant remediation, climate control and flood prevention (Baró *et al*., 2014). More recently, the role of ecosystem services and environmental quality in providing health benefits to individuals and communities has been explored (Summers *et al*., 2014), with ever-increasing evidence that environmental quality is a powerful determinant of a range of human health outcomes, including stress levels (Tyrväinen *et al*., 2014), longevity (Takano *et al.*, 2002) and a range of psychological issues (Fuller *et al*., 2007). Access to a good-quality environment can buffer individuals from the rigours of modern living, particularly in urban settings where these stressors are acute (Maller *et al*., 2005). Indeed, positive effects on individuals' mood and cognition have been noted by simply viewing these environments from a distance (Van Herzele and de Vries, 2012) or even in photographs (Hartmann and Apaolaza-Ibáñez, 2010).

In the Irish context, studies exploring the health/environment interface are particularly relevant. Ireland has suffered, and is currently suffering from, many shocks to its environmental and societal fabric. During the "boom years" there was sustained development pressure on the environment, resulting in degradation of the "green and blue infrastructure" (i.e. vegetated areas and water bodies) throughout the country (EPA, 2012). Following the "bust", the resources to repair and maintain environmental quality have become limited, although the recognition of GBI as an important component for successful and resilient development has increased (Lennon, 2014). Additional shocks were felt at a societal level. Increased urbanisation and sprawl and degraded GBI assets contributed to rises in chronic ill health conditions such as obesity, diabetes (McCarthy *et al*., 2002) and depression (Barry *et al*., 2009). It is thus timely that the health/GBI interface is investigated.

This increased recognition of the importance of environmental quality to human health has prompted vigorous research in this area, with many studies exploring how the GBI of areas can facilitate improved health outcomes for individuals and communities. Two important research strands have emerged: first, those examining the effects of GBI using self-reported health data and, second, those using measured physiological data.

Studies exploring the health effects of GBI using self-reported health data have been conducted at multiple scales, from the individual level up to city level. These studies found that places with substantial GBI have a wide variety of effects on the people who use or who are near these places. These effects include improved feelings of restoration (Korpela and Hartig, 1996; Völker and Kistemann, 2011), increased levels of physical activity (Völker and Kistemann, 2013; Calogiuri and Chroni, 2014; Pearce *et al*., 2016) and improvements in individuals' health perception, all identified as being analogous to increased income or enhanced ageing (Kardan *et al*., 2015).

Beyond improvements in self-reported health and well-being, researchers investigating the health effects of GBI using measured physiological data have reported similar positive results. The presence of GBIs has been shown to reduce stress hormone levels (Tyrväinen *et al*., 2014), lower blood pressure (Hartig *et al*., 2003) and be correlated with improved birth outcomes (Hystad *et al*., 2014) and increased life expectancy (Tzoulas *et al*., 2007).

In addition to health data, be it self-reported or measured, methods of quantifying, categorising and evaluating GBI elements are equally important in these studies. A wide variety of techniques and technologies have been used, including visual interpretation in the field (Unt and Bell, 2014), survey questionnaires (Van Herzele and de Vries, 2012) and geographic information systems (GISs), the use of which has proliferated in these studies (Germann-Chiari and Seeland, 2004; Groenewegen *et al*., 2006; Van Herzele and de Vries, 2012; Kardan *et al*., 2015).

Geographic information system technologies and spatial data sets have the potential to provide powerful tools for establishing robust links between the presence and configuration of GBI elements and health outcomes. Indeed, the very utility of GIS technologies has led to many studies examining health status and/or outcomes in study areas where GIS data on GBI are available, that is, they can be considered to be "GBI led". This study has a significant GIS and geospatial modelling component.

Conversely, very few studies exploring GBI/health interactions appear to be "health led", that is, in which study areas are chosen based on available health data. This is an important gap in GBI/health studies, as health-led studies would allow the targeting of research towards sites of known health anomalies, that is, where health statuses and/or outcomes are significantly divergent from the mean. It is in such areas that the GBI/health interface should be examined to evaluate the magnitude of GBI element effects on health status in study areas at the extremes of the health spectrum.

1.3 Objectives

This research generated five deliverables based on five core work packages (WPs) incorporating the following content, namely:

1. a comprehensive literature review of the health/environment interface with an additional consideration of the integration of GBI elements into the lived environment;
2. identification and compilation of national coverage, fine-scale health databases relevant to this and other spatial research;
3. characterisation of the land cover for the identified sites of interest based on available GBI data sets at relevant scales;
4. identification through statistical modelling of the magnitude of associations of GBI elements with health status within the chosen case study areas;
5. completion of the project final report and the organisation of a stakeholder seminar.

2 Literature Review: Towards a More Holistic Framework for a Health-led Approach at the Green and Blue Infrastructure and Human Health Interface

2.1 Introduction

There is growing evidence that GBIs play a positive role in the improvement of human health (Amoly *et al*., 2014; Mueller *et al*., 2017). However, uncertainties remain regarding the nature and magnitude of the relationship between green and blue spaces and human health (Gascon *et al*., 2015; Smith *et al*., 2017). It is noteworthy that the majority of the current evidence provided by previous research has a bias towards the availability of green and blue spaces and associated GBI data, that is, it is "GBI led" (Wheeler *et al*., 2012; Völker and Kistemann, 2014). This has led to less attention being paid to the effects of confounders (or moderators), mediators (i.e. health-promoting mechanisms), indicators employed for assessments and other determinants of human health within such studies (Maas *et al*., 2006; Duncan *et al*., 2011; Beyer *et al*., 2014). It has also not yet been established if the effects of GBI are short or long term in nature (Völker and Kistemann, 2011; Gascon *et al*., 2015). Many of these studies started from, and were driven by, the availability of data on green and blue space, with subsequent associations with healthy outcomes a second stage of the research. In addition, those associations were often calculated at single scales, within short time scales and based on individual scales of analysis.

This section describes the conceptual framework behind our study, which uses the reverse sequence to that in conventional GBI/health interface studies in that it proposes an approach in which the health outcomes become the starting point, with the GBI data configurations forming the second stage of the sequence. We argue that this health-led approach should start with, and duly account for, long-term health outcomes at different geospatial scales before investigating if the presence or absence of GBI, as well as moderator or cofounder variables, play a role in improving health or otherwise. Such a research framework for a health-led approach should be holistic. It should, *inter alia*, encourage long-term rather than short-term studies (Foley and Kistemann, 2015; Gascon *et al*., 2015) and adopt multiple area-level assessments rather than single scale assessments (Groenewegen *et al*., 2006; Smith *et al*., 2017). It should also consider the effects of indicators (i.e. descriptors used), as well as other moderator and confounder variables (i.e. other variables with considerable influence) (Lachowycz and Jones, 2013; Calogiuri and Chroni, 2014). In order to fully determine the requisite features of a new research framework at the GBI/health study interface, this study reviewed a selection of publications ($n = 30$) to identify current research needs at this interface; these were then built into a new research framework that is essentially health led.

2.2 Materials and Methods

The methodology adopted was integrative in nature but could not be classified explicitly as a systematic review; rather, it had more of a scoping approach (Bell *et al*., 2018). It involved a selection of 30 key recent (most published within the last 10 years) GBI/health publications that could be classified as either entirely "GBI led" or entirely "health led" in terms of empirical analysis or emphasis. Papers that did not fall into these two categories were excluded from the review process. The selected papers were analysed under 13 thematic headings. These 13 thematic headings provided a framework for the identification of research and data needs within the GBI/health study interface; they also informed the direction of future empirical GBI/health research (see Table 2.1). These 13 thematic headings and the choice of 30 selected papers evolved organically from an integrative review process, which involved wider reading of literature on healthy natures, health geographies, landscape architecture and environmental psychology. Given that it was difficult to find any meaningful literature using direct searches for the terms "green and blue infrastructure led" and "health led" using different search engines (Scopus, Google, ScienceDirect, etc.),

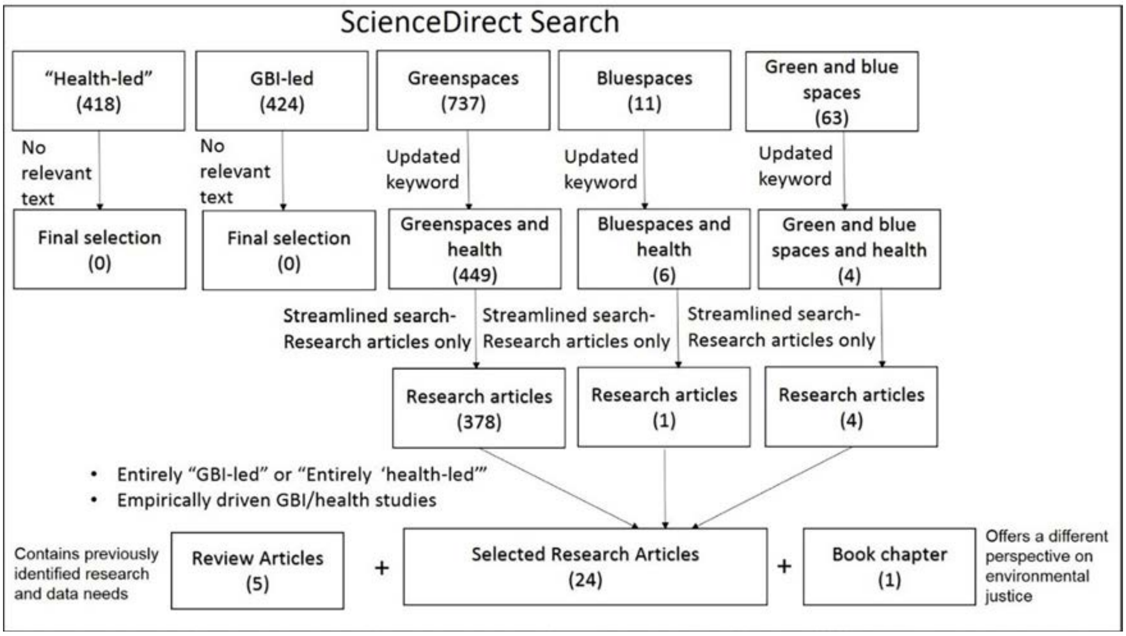

Figure 2.1. Integrative scoping review process adopted in this study.

we developed a more focused and integrative scoping review that involved the selection of original research articles that were classified as either entirely "GBI led" or entirely "health led" (in terms of empirical analysis or emphasis). The original research articles selected were drawn from an initial ScienceDirect search using different initial keywords ("GBI led", "health led", "greenspaces", "bluespaces" and "green and blue spaces") and updated keywords ("greenspaces and health", "bluespaces and health", "green and blue spaces and health"). Some reviews containing previously identified research and data needs and a book chapter offering a new perspective were also added to the review to reinforce the direction of the identified research and data needs. A diagrammatic version of the review process is provided in Figure 2.1.

2.3 Results and Discussion

The results and discussion are divided into two main sections: the results section discusses content under the thematic headings identified (Table 2.1) and the discussion section focuses on the ways in which synthesis of the reviewed literature could specifically inform and support subsequent empirical GBI/health assessments. The literature below is tagged in terms of the numbered themes identified in Table 2.1. In addition, Supplementary Table 1 (available on request) provides a much fuller and more detailed summary of the content of each of the reviewed papers under the 13 different thematic headers. The analysis below is, by necessity, a summary of the content of the papers across the themes.

2.3.1 Results

From the selected literature, a number of specified new options and classifications were identified from the analysis. Under *theme 1*, GBI specification, the literature included work in which green infrastructure and blue infrastructure featured individually, were classified in a mix with each other (i.e. overlapping GBIs) and were classified in a mix with other types of infrastructure (i.e. overlapping green, blue and grey infrastructures). From these papers, a separate green or blue approach also suggested a wider colour palette, with more combinations of GBI being considered for analysis, for example the addition of sand fields, stone quarries and other brownfield sites as brown spaces in GBI/health studies. Additional indirect GBI indicators such as the presence of urban slums (Olajuyigbe *et al*., 2015) (*theme 2*) were also identified alongside conventional indicators related to the structure, size, density, sight and presence of, contact with and proximity to green and blue spaces. These all suggested more nuanced ways of incorporating GBI into GBI/health studies.

Beyond these broad-level papers, a range of papers focused on indirect health indicators that connected

Table 2.1. Information extracted and questions answered under the thematic headings

No.	Thematic headings	Extracted information	Question answered
1	GBI specification	Prevalence of green or blue infrastructure at the GBI/health study interface in literatures	Is there an obvious bias towards green or blue infrastructure at the GBI/health study interface?
2	GBI indicators	List of GBI indicators commonly used at the GBI/health study interface	Are the current GBI indicators effective and sufficient in assessing the GBI and human health association?
3	Health aspects	Health aspects receiving attention at the GBI/human health research interface	Is there an obvious bias towards some health aspects at the GBI/health study interface?
4	Health indicators	List of health indicators used	Are the current health indicators effective and sufficient in assessing the GBI and human health association?
5	Health data categories	Prevalence of categories of health data used at the GBI/health study interface	What health data category is the most prevalent? Are the health data categories commonly used at the GBI/health study interface limited? Is there a need to increase the use of other categories of health data?
6	Methodological approach adopted	Proportion of studies adopting health-led or GBI-led approaches	Is there an obvious bias towards a particular methodological approach?
7	GBI and health association	Proportions of studies that confirm associations at the GBI/health study interface	Is there an obvious bias towards assuming or confirming associations at the GBI/health study interface?
8	Kinds of association	Proportion of confirmation of association at the GBI/health study interface that is hypothetical and evidence based	Are the confirmations of associations at the GBI/health study interface at best hypothetical or mostly evidence based?
9	Statistical methods applied	Proportion of confirmation of association at the GBI/health study interface	Are confirmations of associations at the GBI/health study interface using sufficient statistical methods? Do they have a standard procedure?
10	Moderator or confounder variables assessed	Proportion of studies at the GBI/health study interface that factor in the effect of moderator or cofounder variables, e.g. demographic and socio-economic status	Is there an obvious bias towards factoring in the effect of moderator or confounder variables at the GBI/health study interface?
11	Location/region	Prevalence of GBI/health studies across continents or developing/developed countries dichotomy	Is there an obvious locational or regional bias or developed/developing countries dichotomy at the GBI/human health research interface?
12	Spatial scale	Prevalence of GBI/health studies across spatial scales, i.e. large, medium and small scales or single and multiple scales	Is there an obvious bias towards working at certain spatial scales at the GBI/health study interface?
13	Time coverage	Prevalence of cross-sectional or longitudinal studies at the GBI/health study interface	Is there an obvious bias towards cross-sectional or longitudinal studies? Are there indicators that are sensitive to time coverage?

individuals and groups to both healthy and unhealthy environments (*themes 3* and *4*). One health-specific aspect that emerged was a focus on more socially constructed aspects such as health inequality and neighbourhood access to green or blue space (Comber *et al*., 2008; Mitchell *et al*., 2011, 2015; Calogiuri and Chroni, 2014; Coppel and Wüstermann, 2017; Kabisch and van den Bosch, 2017; Smith *et al*., 2017; Wüstermann *et al*., 2017). This also included more collective dimensions such as sense of social security (Groenewegen *et al*., 2006) and social connectedness and bonding (Asakawa *et al*., 2004; Völker and Kistemann, 2011; Foley and Kistemann, 2015).

From the selected literature, we identified a wide range of direct health indicators that pertained to the wider population, society, environments and landscapes (*theme 4*). Examples of population-based health and well-being included psychological health, child and young adult health, adult obesity and overweight, recovery and restorativeness and expressed preferences (Ode *et al*., 2009; White *et al*., 2010; Völker and Kistemann, 2011; Calogiuri and Chroni, 2014). Here, a broad thesis emerged, underpinned by public health and environmental psychology, that being outdoors in nature was broadly beneficial for health and well-being, in a number of different settings (Frumkin, 2003). Finally, and of special relevance, a number of papers had strongly developed lines of thinking around place-based or landscape-based health and well-being. This included research on healthy places (Frumkin, 2003; Foley and Kistemann,

2015) and landscape ecology and health (Asakawa *et al*., 2004; Ode *et al*., 2009) and more explicit place-focused research on, for example, urban/city/inner-core health and improvement (Neema and Ohgai, 2013; Mills *et al*., 2015; Olajuyigbe *et al*., 2015; Mueller *et al*., 2017).

Given the importance of health data as a key component of health-led thinking, the review also looked closely at papers that contained different forms of health data categories (*theme 5*), as well as measurements of health outcomes. Those that featured in the selected papers included data from physical measurements (e.g. vegetation census, ambulatory blood pressure measurements) and self-reported indicators (from surveys, interviews, focus groups, semi-qualitative studies, discussion groups, visual stimuli/attention experiments, photo-elicitation, questionnaires, participant observation, etc.). A number of the papers also featured what might be termed “proxy health data”. Sources of proxy health data included census data incorporated into GISs (Comber *et al*., 2008; Mitchell *et al*., 2011; Kabisch and van den Bosch, 2017; Wüstermann *et al*., 2017), multiplier models (Mills *et al*., 2015) and GIS-derived indicators (Smith *et al*., 2017). In addition, specific attention was paid to other less quantifiable health data (including ethnographic and other qualitative forms) identified in a range of review papers (Frumkin, 2003; Lachowycz and Jones, 2013; Calogiuri and Chroni, 2014; O’Brien and Morris, 2014; Foley and Kistemann, 2015).

As noted, a key methodological approach was the identification of papers as being either GBI led or health led. All studies either confirmed or assumed associations at the GBI/health study interface. The confirmation of association by all studies was both evidence based and hypothetical in nature (*themes 6, 7* and *8*). These associations were evident in a mix of social and environmentally focused work and examples included religious and ethnic groups’ accessibility to green space (Comber *et al*., 2008), the presence/absence of slums (Olajuyigbe *et al*., 2015), pollutant removal and air quality improvement (Neema and Ohgai, 2013; Mills *et al*., 2015), water quality and safety improvement (Asakawa *et al*., 2004; Neema and Ohgai, 2013), urban climate improvement, that is, urban cooling and saving of energy (Neema and Ohgai, 2013), and feelings of social safety and exposure to environmental hazards (Groenewegen *et al*., 2006; Smith *et al*., 2017).

A number of the GBI-led papers tended to have an economic focus, including papers on increased recreational and economic property value (Neema and Ohgai, 2013; O’Brien and Morris, 2014) and economic savings on health (Mitchell *et al*., 2015; Mueller *et al*., 2017). However, some of these papers also blurred their interest between economic and health benefits, especially those that focused on landscape perception and preference (in terms of attractiveness, willingness to visit and pay, perceived connectedness and restorativeness) (Ode *et al*., 2009; White *et al*., 2010; Völker and Kistemann, 2011; O’Brien and Morris, 2014). Finally, in a subtle shift towards health-led thinking, although still built around the GBI side, well-being emerged as an important association, with emphasis on the opportunity for physical activity, participation, enhanced contemplation, anger reduction, positive affect/emotional bonding, education and learning (Hartig *et al*., 2003; Fuller *et al*., 2007; Calogiuri and Chroni, 2014; Völker and Kistemann, 2014) and sense of place (Frumkin, 2003; O’Brien and Morris, 2014).

The major statistical methods identified in the wider literature for confirming associations at the GBI/health study interface were also observed in this review (*theme 9*). These included different forms of analysis of variance (ANOVA) (e.g. one-way ANOVA, two-way ANOVA), different kinds of correlation analysis (e.g. correlation coefficient, non-parametric Spearman rank correlation coefficient) and various implementations of regression modelling (e.g. linear, multi-level linear, logistic). Spatial analysis using remote sensing-based operations, for example normalised difference vegetation analysis, post-classification comparison analysis and image classification/characterisation, as well as GIS-specific operations, were all used in the visual analysis of such relationships. Associated adjustment/complementary methods were also used in the course of quantitative assessments that incorporated scatterplots, age/sex standardisation and multi-collinearity tests. Alongside the use of statistical methods, some studies employed literature reviews and qualitative comparisons to describe or assume relationships at the GBI/health study interface and these were also included in the review, as they informed the wider thinking behind the project. A detailed breakdown of the studies that employed statistical methods and those that relied exclusively on literature reviews and qualitative comparisons is available on request.

Some of the reviewed papers did not account for moderator and confounder variables at all, with most studies that did consider them focusing only on demographic and socio-economic factors (*theme 10*). This review classified other relevant moderator and confounder variables found in GBI/health literature into spatial and neighbourhood factors, environmental factors, cultural factors, longitudinal factors and other health and health-promoting factors. Specific spatial and neighbourhood factors considered included urbanity/rurality (or urban/rural status), rates of crime and access to social and cultural services, for example cinemas, theatres and cultural centres (Wheeler *et al*., 2012; Beyer *et al*., 2014; Mitchell *et al*., 2015). Identifiable environmental factors included in the review were the types, sizes and densities of green spaces, climate, living context/settings, etc. (Hartig *et al*., 2003; White *et al*., 2010; Wheeler *et al*., 2012; Lachowycz and Jones, 2013). The only cultural factor included in the review was language (Ode *et al*., 2009). Other relevant cultural factors in this respect may include legal frameworks, governance systems, health habits and planning cultures enshrined in the ways of life of the local and regional people involved (Calogiuri and Chroni, 2014; Pearson *et al*., 2014). An example of a longitudinal factor identified in the review was length of residence (Groenewegen *et al*., 2006). Other health and health-promoting factors included were physical activities or tasks, alcohol consumption, fruit and vegetable consumption and preterm birth (Asakawa, *et al*., 2003; Amoly *et al*., 2014; Calogiuri and Chroni, 2014; Pearson *et al*., 2014; Mueller *et al*., 2017).

In considering the importance of geographical context, most studies had specifically identifiable location(s) and spatial scale(s) of assessment (i.e. local, regional, national, international and global) (*themes 11* and *12*). These varied from micro-scale studies to city-level comparisons across a number of European countries. Several of the more review-based studies, however, had no specific location or spatial scale of assessment, but rather considered multiple settings (Frumkin, 2003; Lachowycz and Jones, 2013). They were therefore termed “not region specific” or “not scale specific” respectively. In addition, the time coverage of most studies were either cross-sectional or longitudinal in nature, although it was also noted that longitudinal geospatial evidence, especially health led, was limited and likely to be problematic. The time coverage of some studies was limited, given that they described GBI and human health relationships historically without being supported by concrete quantitative evidence (Frumkin, 2003; Foley and Kistemann, 2015).

2.3.2 Discussion

The synthesis of this review and the identified research and data needs and directions are documented in Table 2.2. The previous section identified a range of relevant themes that informed wider work on this topic and these were also synthesised to identify how they might specifically inform or be realistic within the current study. To be effective at small as well as large scales, it was important to be realistic and consider data gaps and, in turn, augment the literature through a consideration of this within specific approaches used in the current study. Table 2.2 provides broad statistics on the relative proportions of papers relating to the different components of each theme. For example, under *theme 1*, GBI specification, the relative importance of “single-shade” and mixed palettes gives an immediate indication of the relative dominance of green infrastructure studies (around 67%). The final column in the table summarises data gaps, indicating possible ways forward for future work more generally.

Overall, the literature suggested that there were few studies assessing the health impacts of blue infrastructure individually, as well as overlapping GBI or overlapping green, blue and grey infrastructure within the same frame. Consequently, more holistic studies that assess the health benefits of blue infrastructures, as well as their overlap with green and grey infrastructures, should be incorporated into new research frameworks at the GBI and human health interface. This would not only present a more holistic picture of the health benefits of constituent green, blue or grey infrastructure *in situ* but would also contribute to the robustness of the analysis. Additionally, studies on blue infrastructure tended to be more qualitative than quantitative; further quantitative blue infrastructure and health interaction studies are required and represent a largely open research field waiting to be explored.

Table 2.2. Synthesis of the review analysis and research/data needs identified

No.	Thematic headings	Sub-headings	Synthesis, *n* (%)[a]	Identified research and data needs
1	GBI specification	Green infrastructure	22 (66.7)	Limited studies on blue infrastructure. Limited research on the magnitude of health benefits conferred by an overlap of GBI
		Blue infrastructure	3 (10.0)	
		GBI	4 (13.3)	
		Green, blue and grey infrastructure	1 (3.3)	
2	GBI indicators	Direct indicators	29 (96.7)	Limited studies used indirect and proxy indicators, even though they are innately connected to direct indicators. Indicators not sufficient even though effective
		Indirect indicators	1 (3.3)	
3	Health aspects	Population-based health aspects	21 (70.0)	Less attention on landscape-based health aspects
		Society-based health aspects	22 (73.3)	
		Landscape-based health aspects	4 (13.3)	
4	Health indicators	Direct	16 (53.3)	Limited use of proxy indicators. Indicators not sufficient even though effective
		Indirect	19 (63.3)	
		Proxy – not used in reviewed papers	0 (0)	
5	Health data categories	Physical measurement	5 (16.7	Limited use of data from physical measurements and proxy health data
		Self-reported	20 (66.7)	
		Proxy health data	4 (13.3)	
		Previous publication and review	6 (20.0)	
6	Methodological approach adopted	GBI led	26 (86.7)	Limited health-led studies
		Health led	4 (13.3)	
7	GBI and health association	Confirmed	17 (56.7)	More studies confirm GBI and health association. More confirmation still needed
		Assumed	13 (43.3)	
8	Kinds of association	Evidence based	28 (93.3)	More studies are evidence based. More still needed
		Hypothetical	2 (6.7)	
9	Statistical methods applied	ANOVA	5 (16.7)	Statistical methods are frequently used for confirmation of GBI and health association. There are, however, no standard procedures for confirming GBI and health association
		Correlation	3 (10.0)	
		Regression	10 (33.3)	
		Spatial analysis	13 (43.3)	
		Adjustment/complementary methods	8 (26.7)	
		Mix of statistical tests and spatial methods	8 (26.7)	
10	Moderator or confounder variables assessed	Demographic factors	15 (50.0)	Assessment of the effects of moderator and cofounder variables is omitted by some studies. Less emphasis on spatial and neighbourhood factors, environmental factors, cultural factors, longitudinal factors and other health and health-promoting factors
		Socio-economic factors	13 (43.3)	
		Spatial and neighbourhood factors	4 (13.3)	
		Environmental factors	5 (16.7)	
		Cultural factors	1 (3.3)	
		Longitudinal factors	1 (3.3)	
		Other health and health-promoting factors	6 (20.0)	
		Unaccounted for	10 (33.3)	
11	Location/region	Europe	23 (76.7)	Limited studies in developing countries, especially in Africa, Asia and South America
		North America	3 (10.0)	
		Asia	2 (6.7)	
		Australia/New Zealand	4 (13.3)	
		Africa	2 (6.7)	
		South America	1 (3.3)	
		Developed countries	25 (83.3)	
		Developing countries	3 (10.0)	
		Not region specific	2 (6.7)	

Table 2.2. Continued

No.	Thematic headings	Sub-headings	Synthesis, *n* (%)[a]	Identified research and data needs
12	Spatial scale	Local	14 (46.7	Mostly single-scale assessments at large scale
		Regional	1 (3.3)	
		National	6 (20.0)	
		International	7 (23.3)	
		Global	1 (3.3)	
		Not scale specific	2 (6.7)	
13	Time coverage	Cross-sectional	28 (93.3)	Limited longitudinal studies. Indicators sensitive to time coverage are still scarce. Moderator and confounder variables sensitive to time coverage are yet to be widely used
		Longitudinal	1 (3.3)	
		Historical	2 (6.7)	

[a]Number (percentage) of papers compared with the total number of papers reviewed ($n = 30$).

Most of the reviewed papers used direct GBI indicators, that is, GBI indicators that were related to structure, size, density, sight and presence of, contact with and proximity to green and blue spaces. In order to ensure more holistic and robust assessments going forward, indirect and/or proxy GBI indicators should be allowed to feature alongside direct indicators in GBI/health studies. An example of indirect GBI indicator usage is the use of land use changes/conversion as an indicator for lack of accessibility to green spaces (Olajuyigbe *et al*., 2015). The use of indirect indicators could be particularly relevant in instances in which data are or access to data is limited. An example of a proxy GBI indicator from the wider literature considered was the Walk Score. Duncan *et al*. (2011) tested and ascertained the effectiveness of such a score as a proxy indicator for relative accessibility to green spaces.

Most health and well-being aspects assessed at the GBI/health study interface were population and/or society based. More specifically, landscape-based health aspects need to be more fully assessed within GBI/health studies. This would be advantageous for sustainable planning, as it would deepen the evidence base by extending its scope to landscape levels. In choosing an approach that built out from health data and fed this through to parallel indicators of biodiversity, urban greening and more specifically “therapeutic” landscapes, the scope of the research would be extended in these directions (Foley and Kistemann, 2015).

Although GBI/health studies have primarily used direct health indicators from physical measurements and self-reported health in the past, there has been a notable rise in the use of indirect health indicators. This is particularly important for developing countries where health data are limited (Neema and Ohgai, 2013; Olajuyigbe *et al*., 2015), as well as some developed countries where access to direct data is difficult because of privacy laws (e.g. Ireland). The use of proxy health indicators (e.g. inequality or deprivation indices) is still relatively limited. The use of such indicators should be encouraged because they provide composite information that incorporates several important health-determining variables, although one would always need to be careful of their role as confounders (Lachowycz and Jones, 2013). Noteworthy also was the low proportion of health data from physical measurements compared with self-reported data, a subject of particular concern for environmental psychologists. New research designs that include an increase in the use of physical measurements alongside self-reported data would reduce subjectivity associated with health data at the GBI/health study interface and provide more directly triangulated data.

Methodological approaches adopted at the GBI/health study interface have been overwhelmingly GBI led. There is undoubtedly a need for the adoption of more health-led approaches. The trend at the GBI/health study interface is based more on confirming associations than assuming them. Such associations are clearly also evidence based rather than hypothetical in nature. Different studies used a variety of statistical methods ranging from ANOVA to correlation, regression modelling and spatial analysis, as well as adjustment and complementary methods.

This review observed the frequent use of ANOVA and correlation testing for assessing the effects of socio-economic and demographic moderator and confounder variables. Remote sensing and GIS analysis were mostly used for quantification of GBI indicators and assessing the effects of spatial and neighbourhood moderator and confounder variables, as well as visual analysis of associations at the GBI/health study interface. Subsequent research frameworks should reflect an adequate understanding of the interoperability of the statistical methods used. There is therefore a need for standardised procedures in combining different forms of statistical methods for improving research outputs at the GBI/health study interface. Such standard procedures should clearly motivate the use of the different individual statistical methods to enhance reproducibility, as the increasing lack of reproducibility of scientific studies is a cause of growing concern (Benjamin *et al*., 2017). The effects of moderator and confounder variables at the GBI/health study interface are often neglected. When considered, the emphasis was usually more on demographic and socio-economic variables. Other important moderator and confounder variables such as spatial and neighbourhood factors, environmental factors, cultural factors, longitudinal factors and other health and health-promoting factors deserve more attention at the GBI/health study interface, although may be beyond the immediate scope of this study. Additionally, the assessment of spatial/neighbourhood factors, environmental factors and longitudinal factors requires multi-temporal, higher spatial resolution remote sensing and GIS data that can be made available by geographers and other experts in the field (Germann-Chiari and Seeland, 2004; Groenewegen *et al*., 2006; Mills *et al*., 2015).

Additionally, most studies (even comparative studies identified in the review) were carried out at a single spatial scale, whether that be local, regional, national or international. In order to improve knowledge gained from studies at the GBI/health study interface, especially in designing health interventions within the framework of land development and planning, there remains a need to explore more deeply the associations across multiple scales, especially given the impact of modifiable area units on statistical results (modifiable areal unit problem, MAUP). Such multi-scale assessment could include lower scales of assessments such as census tracts, electoral districts, settlements and parcel-by-parcel assessments (depending on the resolution of the available data), as well as health-specific administrative units. Publicly available, spatially referenced, high-resolution health data with consistent units of measurements and presentations, as well as varieties of GBI and health indicators, will be needed for such rigorous multi-scale assessments. This study will explore some of these in an Irish setting, but with evident translatability to other geographies in other countries, especially in the Global South where such work could be valuable but is currently underdeveloped.

Many studies at the GBI/health study interface were also cross-sectional in nature (for single time periods). This did not allow for time series assessment of the long-term effects of GBI on human health. Although there were a few historical studies, a new research framework at the GBI/health study interface would benefit from longitudinal studies using GBI and health data in combination, as well as moderator and confounder variable data collected and analysed over time (Pearce *et al*., 2016). Such studies will still require new kinds of data and indicators beyond those in current use. Publicly available, spatially referenced, high-resolution longitudinal GBI and health data with consistent units of measurements and presentations will be required for such kinds of studies. New GBI data and indicators suitable for longitudinal studies will also be likely to include higher resolution time series data on land cover/use (with change in land cover/use as an indicator), time series data on the Normalised Difference Vegetation Index (NDVI; with change in NDVI as the indicator), etc. New data platforms, such as the European Space Agency’s Copernicus Open Access hub and Google’s Earth Engine, which provide users with free online tools to extract such longitudinal GBI data, may facilitate such data collection, although these are being slowly developed. Health data and indicators for longitudinal studies, especially at survey scales, may include the means to map out progressive improvements in health conditions (physical, mental or psychological), residency-related change in health conditions, etc. Other moderator and confounder variables emerging for longitudinal studies may include length of residence, change of residency, regularity or change in workplace–home transportation patterns, change in financial status, change in gender orientation, change in marital status, change in religious beliefs, ageing and seasonal change in weather/climate. Although these will require complex and well-ordered data collection, there is a shift in this direction, as noted in section 3.2.8.

2.4 Conclusion

There is a large body of evidence-based research that has confirmed that GBI impacts positively on human health. However, a fuller evidence base is still required to extend the identified research and fill the data gaps at the GBI/health interface. Health-led methodological approaches for assessing such associations still require significant exploration. In devising a more holistic framework for such health-led approaches, this review identified important research and data gaps that can direct subsequent studies at the GBI/health study interface. If these gaps are filled, the robustness and acceptability of GBI/health research results could be significantly improved. Such identified research and data needs include:

- more studies analysing the effects of blue infrastructure on human health;
- an assessment of the effects of overlapping GBIs or overlapping green, blue and grey infrastructure to provide a more holistic and accurate representation of the magnitude of health benefits derivable from them;
- subsequent studies that not only consider population- and society-based health aspects but also extend this to landscape-based health aspects;
- an increase in the use of indirect GBI indicators, as well as proxy health indicators, to provide more robust information on the magnitude of health benefits of GBIs;
- an increase in the amount of directly collected and individual-level health data to help reduce the subjectivity associated with self-reported health data;
- the use of proxy health data that contains composite health information (e.g. health inequality data) to also help improve future analysis at the GBI/human health research interface;
- more publicly available, spatially referenced, high-resolution longitudinal health data with consistent units of measurements and presentation for rigorous multi-scale and longitudinal assessments at the GBI/human health research interface;
- prioritisation of the assessment of the effects of moderator and confounder variables, particularly demographic, neighbourhood, environmental, cultural and longitudinal factors, alongside other health and health promoting factors;
- standard procedures for the application of statistical methods at the GBI and human health research interface;
- prioritisation of multi-scale assessments, especially at finer spatial scales (e.g. electoral districts, settlements, parcel by parcel), for sustainable planning of health interventions in physical development;
- more case studies from developing countries, especially in Asia, Africa and South America, to come to a global consensus on the role of GBI in improving human health;
- lastly, rapid development of GBI indicators, as well as health indicators sensitive to long-term effects of GBI on human health.

Although mindful that this Irish study has made progress on only a number of these themes, specifically those related to increased emphasis on place type, the use of multi-scalar geospatial data (measured, self-reported and proxy) and the use of a visible place-based longitudinal component, the list above opens up space for a much wider research agenda that fills the gaps between individual-level and national-level measures. In addition, while maintaining the focus on nature and its potential role in human health and well-being, it starts out from a different position, which builds on the geographies of health to produce a specifically spatial vision for research on the GBI/health interface.

3 Data Audit

3.1 Introduction: Identifying Health Data

This study had a very specific focus on the use of health data to drive the modelling, central to its identification as a piece of "health-led" research. Given this focus, it was important to determine what health data were available and in what forms and formats, to start a core health data audit. In addition, data that could be classified as being "geospatial" were of particular relevance, specifically in terms of providing indicators of broad health outcomes for different geographical areas. Finally, a critical assessment needed to be made on data usability for a short-term 1-year project, based primarily on acceptable scale and comparability as well as critical assessments of each individual data set in terms of its capacity to be "made spatial" and to be relatively accessible in that tight timescale. This will be the focus of this section of the report. Although the choice of sample/case study sites was originally included in this section on the design of the project, we have shifted the discussion of the choice of sample/case study sites into the next chapter. Although the health-led component was central to the choice of sample/case study sites, it also made sense to consider the final choice of study locations in relation to the available GBI data. Therefore, the detailed discussion of that choice and the data modelling requirements are more fully discussed in Chapter 4.

This summary is not intended to act as a full audit of health data in Ireland and as such auditing takes place across a wide range of clinical, service and patient-oriented settings and across different sectors of the health-care system. In addition, there has already been a considerable effort put in to developing health intelligence within the Health Service Executive (HSE), Health Research Board (HRB) and Department of Health, with the work of the Health Intelligence Unit (HIU) especially important through the development of Health Atlas Ireland, which acts as a service-oriented data repository with a significant geospatial component. We were also guided in our audit by exploring what types of data, commonly used in wider international studies, might be available in Ireland for the kinds of cross-sectional and associational research approaches used in this study. We also had to bear in mind the wider structures around which health data – almost always a sensitive data product – have been made available to public researchers in Ireland, although there have been some significant recent initiatives in this area.

In truth, much of this work has already been carried out through the Health Information and Quality Authority's (HIQA) *Catalogue of National Health and Social Care Data Collections*, version 2.0 (HIQA, 2014). This comprehensive and rolling cataloguing of 107 data sets covers everything from very specific clinical data to publicly available data such as the census and key statistics published by the Department of Health. The metadata is organised around 16 different fields and, for the purposes of this audit, key fields include the data set name, the data holders' website addresses, data content, coverage, source frequency and access protocols.

Access to good-quality health data, in particular at meaningful levels of spatial detail, remains an ongoing issue. One important objective of this audit was to identify data that had a *spatial tag* and that was relatively accessible for researchers. This was quite separate from any discussion about mechanisms that might improve data access to the satisfaction of both data holders and data users. An especially comprehensive recent document in this regard has been the HRB's report, *Proposals for an Enabling Data Environment for Health and Related Research in Ireland* (Moran, 2016). This report, often referred to as the DASSL report, looked more closely at the complexity and mechanics of access, storage and linkage that might more fully develop the use and, by extension, the societal benefits of better access to health data. A key recommendation of the report was the development of protocols including effective "safe havens" for access to sensitive health data and we will briefly return to those discussions below. Given the recent push for more open data access, especially through initiatives such as INSPIRE and the Open Government initiative, we are beginning to see the listing and initial dissemination of previously hard-to-access data sets. However, such initiatives are still in their infancy and hence the concern for correct protocols and mechanisms to allow for that access. Initiatives such as the Environmental Protection Agency's SAFER resource (EPA, 2014) and a separate GIS-specific data portal, [http://gis.epa.ie/ (accessed 11 September)] are both key sources of data, especially in relation to the auditing of environmental health data, and these are discussed in more detail in section 3.2.7 below. However, in all cases, there is a sense that the *spatial dimensions* of data, especially for health-specific subsets, need more specific attention. This is a key contribution of this audit compared with earlier audits.

3.2 Health Data: Contexts

3.2.1 International context

Typically, health data can be gathered and shared across multiple settings and scales. Globally, data are collected for international comparisons, although these are complicated by different cultural understandings of the collection, value and use of health data. Although constrained by national collection priorities, the World Health Organization reports core measures of life expectancy and causes of death at the national level, as these are consistently collected across the world. Data on health service provision are also gathered, although there are gaps in these data. At a European scale, the range and extent of health outcome data increases and, across the European Union (EU), national- and regional-level summaries for similar indicators are gathered, when possible annually, within Eurostat summaries. As well as general population health indicators, there are also service-specific data but these are less relevant here. Overall, data are collected longitudinally but from a geographical-scale perspective; they are at national or, at best, NUTS II (large regional) level, and these are too crude to work with for this project's needs.

3.2.2 National context

At a national level within Ireland, health-related data have been collected and used in a number of different ways, mostly driven by strategic policy (Department of Health and Healthy Ireland) and the requirements of the delivery of public health services (HSE). As a member of both the EU and the Organisation for Economic Co-operation and Development (OECD), Ireland is required to return standardised data for comparative purposes. In the case of the OECD, the annual Health at a Glance report summarises data around health status, determinants, services, access, quality and funding and also feeds into EU national-level reporting. These data are typically derived from Ireland's own internal statutory data sets, which are collected annually across the different health sectors and then fed in to such reports. Although there has been considerable movement towards producing health data across new information technology-driven models, these are still relatively underdeveloped, especially in relation to their geospatial potential, with any level of geographical detail being substantially absent.

Within Ireland, many of the health data collected have a strong focus on public health and the management of services at primary, community and secondary levels. Internally, the HSE regularly publishes the report *Health in Ireland: Key Trends*, usually in December of each year, which provide statistics on an annual summary basis, using regularly collected administrative data (Department of Health, 2017). These reports have not traditionally been published to any level of spatial detail, although they do contain useful spatial data on topics such as General Medical Services (GMS) (medical) card holding and wider reimbursement schemes. However, the 2017 report took advantage of the availability of 2016 census data to show maps of disability and ageing at small-area (SA) scale, as well as representative county-level mortality data. Indeed, for the first time ever, information from these sources has been made available via data.gov.ie, including data derived from the Hospital In-Patient Enquiry (HIPE) system on hospital and condition-specific waiting times across the past 4 years. Although focused on the individual hospital scale, this represents progress in terms of making service-level data with a geographical focus available in a clearly accessible way.

Other data are also being made available via web portals, of which a good example is data gathered and made available by the Institute of Public Health (IPH) via its Public Health Well service. This cross-border agency has traditionally shared administrative and survey data across a wide range of health topics. Within the Health Well, the established Public Health Information System (PHIS) provides some county-level information on mortality, cancers and hospital activity, as well as more aggregated information on fertility and psychiatric services. Although data in such portals have some geographical nuance, it rarely goes too deep, although it has been suggested that such data are slightly richer in Northern Ireland, in part because of the longer embedding of a postcode as a proxy address since the mid-1970s. The recent arrival of Eircode in Ireland may open new routes for access to quality health data at a detailed geographical scale.

3.2.3 Geospatial context

For the purposes of this research, one essential pre-requisite was that any data used should have a spatial tag. This did not need to be a specific numerical identifier of location, such as a co-ordinate like latitude/longitude; however, it did have to contain some sort of location field and identifier that allowed the data to be made spatial and mapped in digital form. From a geospatial modelling perspective, a spatial tag can run from a national or regional identifier/name, right down to the individual scale through personal details and/or a home address. The focus of this data audit was to initially identify data sets that already had or had the potential to be quickly given a spatial tag, ideally at as fine a scale as possible. It is also a feature of geospatial data that they can be collected at both areal and point scale but can be easily compiled and aggregated within GISs into wider administrative geographies. As such, there was always a focus on the "geospatial" potential of any data set and this was built into the critical assessment discussed further below in section 3.3.1.

3.2.4 Access and privacy issues

Any mention of individual patient data makes people in the health sector and general public rightly nervous. This concern is at the heart of the discussions in the DASSL report and it is a fundamental ethical position that no health information on any individual should be published in any public way without consent, to protect patient anonymity. Medical records from the primary and secondary sectors include specific clinical and other illness management data on individuals. While wider discussions on a patient identifier are ongoing, it is certainly the case that such data should never be published as identifiable dots on a map. Nevertheless, the potential for such data is still considerable, as it is these data that can be protected in aggregated summaries developed within geospatial modelling. This idea of summary point data, aggregated to areas or polygons, has strongly informed the data audit thinking for this project. Some longitudinal survey data sets, discussed in section 3.2.7 below, have clear potential for conversion via address matching but can then be re-aggregated to acceptable area-based reporting scales. Such thinking underpins address matching using existing services such as GeoDirectory and the newly introduced Eircode. Although individual-level data, even from surveys, did not form part of this study's data modelling, the use of these data as an important potential data-sourcing route is noted, if collected, coded and mapped to an agreed spatial scale for modelling and analytical purposes.

3.2.5 Scale and comparability (data-matching) issues

Another key aspect of this project was the requirement for data to be potentially comparable across time and scale. This was especially important to a data auditing approach, and specific elements of comparability are crucial to effective data matching. This applied especially in a project in which there was a specific intent to carry out multi-scalar modelling across different time periods. As noted above, however health data are collected, they are often published at an aggregated scale, typically using established areal units such as those used for administrative purposes, for example census geographies [local authority (LA), local electoral area, settlement, electoral division (ED) and SA], but also within the health sector, for example community health-care organisations (CHOs, $n=9$), local health offices (LHOs, $n=33$) or proposed primary care networks (PCNs, $n=$c90), which may (their development is ongoing) provide geographical planning units of around 50,000 people across the country (Figure 3.1 shows a putative geography for the Mid-West region).

The historical development and maintenance of geographical units has always been an important issue, both in relation to co-terminosity of boundaries across scales and for comparability over time. At the same time, new geographies are derived or developed that can be driven by policy initiatives or the development of new services associated with population growth. Keeping boundaries stable over

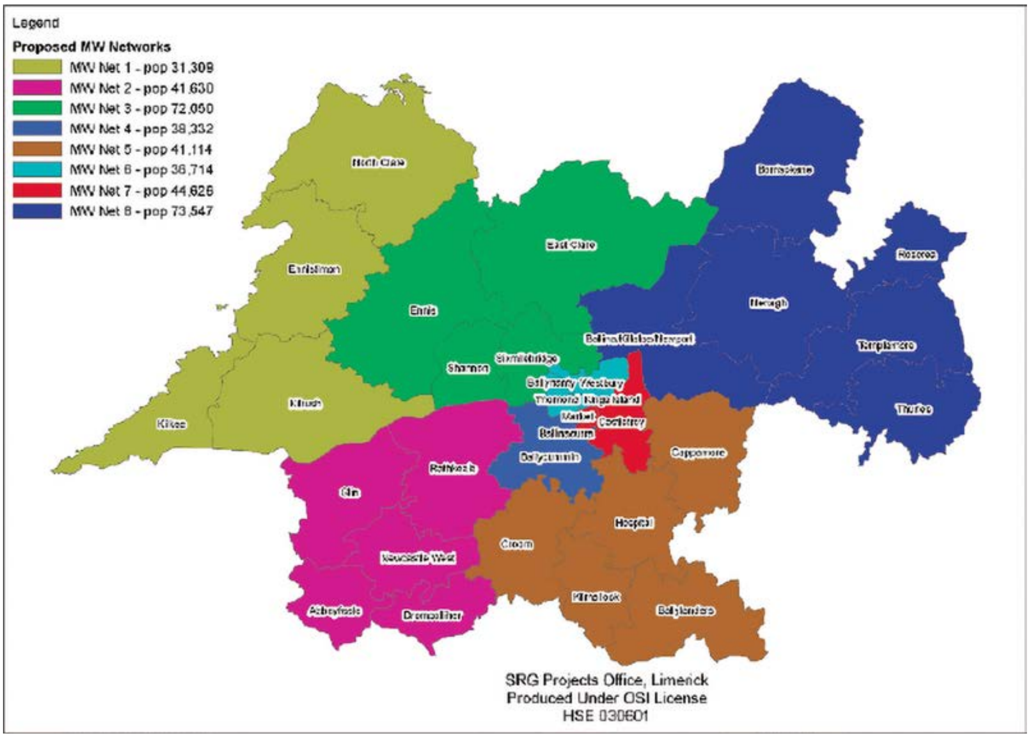

Figure 3.1. Proposals for PCNs: sample for the Mid-West. Source: CHO Mapping Office Health Service Executive, under OSi Licence HSE030901HSE.

time is never easy but the importance of keeping them co-terminous as much as possible, that is, nested and non-overlapping, is a key principle. Discussions around the creation of the new census SAs in 2011 (as subdivisions of existing EDs) (Fotheringham *et al*., 2008) or around the design of new CHOs in 2014 (HSE, 2014), where boundaries used in primary care, hospitals networks and mental health had to be somehow knitted together, provide relevant Irish examples. In addition, it is almost always the case that, between different time periods, demographic changes in population distributions, as areas gain and lose populations, mean that boundaries have to be changed and re-aggregated in slightly different ways. Between 2011 and 2016, for example, it is estimated that around 8% of the SA boundaries have changed. The reasons for this vary but typically it would be because of the building of a new housing estate or, especially in rural areas, a reduction in population size below the accepted privacy limits for publication.

However, on another level, the existence of meaningful aggregated geographies also has considerable potential for the collection and use of health data in Ireland, including data on health outcomes. National-level surveys, such as the QHNS, Irish Health Survey (European Health Interview Survey) and new Healthy Ireland Survey, routinely note the addresses of interviewees. This is equally the case with longitudinal surveys such as the Growing Up in Ireland (GUI) study and The Irish Longitudinal Study on Ageing (TILDA). A greater attention to geo-referencing has opened considerable potential for investigations of the role that environments play in shaping individual health over time and there has been a huge growth in research on using survey data in this way, discussed in section 3.3.1. Concerns over breaches of privacy tend to be covered by the aggregation of individuals into reporting areas or, indeed, analyses that use much broader descriptions of place characteristics, that is, urban, suburban, semi-rural, remote, etc. The flexibility and statistical robustness of area-based analyses that are built up from individual-level data are considerable and indeed much of the data used in this project have been collected in this way. In effect, this is what census data are: aggregations of individual/household returns to levels acceptable for public reporting. However, an increased focus on attaching "spatial tags" to routinely collected administrative data and improved mechanisms for attaching them is also building momentum, especially through open data routes such as data.gov.ie.

3.2.6 Census geographies

As a starting point for a public data audit, the Irish census provides a core building block. In operation since 1821 as a decennial census, recent decades have seen it move to a 5-yearly collection cycle, a rare example in the modern world. Data have been collected at multiple scales, 11 in total, with key examples noted in footnote 1.[1] These are made available on a rolling thematic timetable via the Small Area Population Statistics (SAPS), as well as through an interactive portal, StatBank. SAPS data also include digital base maps associated with each geographical unit. They have made the matching between maps and data tables easier to carry out with the introduction in 2016 of a unique spatial identifier called a Global Unique Identifier (GUID) for each individual geographical unit/area.

For this study, the ability to access and publish health-related data for a number of scales, especially at SA and ED levels, was crucial. Data on self-reported health were collected for the first time in 2011, which was also the year that SA-level data – effectively estate-level geography – were first published. As well as new self-reported health questions, data on disability, impairment and caring have been regularly collected for a number of censuses, although some of these data are not made fully available via SAPS. In addition, data from the census at ED and SA scale have been the fundamental building blocks from which the state’s two key deprivation indices, the Pobal HP-Deprivation Index (Haase and Pratschke, 2017) and the Small Area Health Research Unit (SAHRU) Deprivation Index (SAHRU, 2013), have been developed. ED geographies can also be used as the building blocks for higher-level aggregations and one of the newer data sets on mortality was independently constructed using clusters of EDs built up into intermediate areas (IAs, $n = 407$; Rigby *et al.*, 2017).

In general, the ability to nest data inside hierarchical units is important and the capacity to take the same raw data and look at them at different aggregations is an advantage for comparative work, although in statistical terms a potential problem as well. One key error, the MAUP, affects how different scales and zones of aggregation affect statistical summarisation. In particular, MAUP effects show that, the larger the number of units or areas, the wider the data range is likely to be. Additionally, spatial measures of association, such as regressions and correlations, produce lower values as the resolution of the data increases. This was one reason to consider a number of different data sets, working at different scales, in the reporting for the project.

3.2.7 Sources and ownership

Access to health data can be an especially complex process and, indeed, much of the data on health, such as patient records, health conditions, morbidity and other health outcomes, are confidential and owned by a mix of public and private service operators as well as research institutions. As noted previously, the focus of much data collection in health is on service and operational aspects, financial management and the different regulatory requirements associated with evaluation and quality review. Although these did not necessarily inform the detailed analysis associated with this project, the issue of data ownership remains central to any data audit. The HRB data project (DASSL report) provides a thorough background to these issues and suggests a specific model, a Research Data Trust (RDT), based on international best practice, to ensure a safe environment for data sharing and enhanced access into the future (Moran, 2016, pp. 1–6).

In thinking about data access, it is also important to recognise the specific nature of the Irish health-care system, which is effectively a hybrid system with both public and private operators. Most general practices in Ireland are private businesses, which generate income from private patients yet which are also contracted by the state to provide services to citizens who are considered eligible for subsidised state support via the medical (GMS) card. For some practices, this provides a substantial proportion of their income and, indeed, broad-level national data on these payments are provided via the key statistics publication each year. However, arguably, if one wished to do meaningful health monitoring work over time, one would ideally have access to practitioner data for individuals, which would be impossible to negotiate access to for public

1 Key examples of such scales include LAs ($n = 31$), local electoral areas ($n = 131$), settlements ($n = 846$), EDs ($n = 3409$) and SAs ($n = 18{,}641$), as reported in the 2016 census.

or private patients. This also applies at secondary care (hospital) level, where a similarly hybrid and complex public/private mix operates. In this sense, we can only ever access one part of the health data record, which further emphasises the value of imperfect but comprehensive national sources such as the census.

3.2.8 Policy dimensions

Much public policy, from national level to the new regions and on down to LA or service-specific levels, is dependent on good-quality data to provide the evidence and knowledge that it needs to function. Spatial data continue to be used to inform policy in many different ways, primarily for reporting, evaluation and monitoring and increasingly for relative activity and performance. The collaboration between the Eastern and Midlands Regional Assembly (EMRA) and the All-Ireland Research Observatory (AIRO) at Maynooth to produce regional-level interactive mapping is an example of such an initiative. Again, one might argue that detailed-level geographical data are not especially visible in health policy, although they clearly work away in the background to inform it. Better data create better evidence, which means better research, and, while there are good initiatives in place to ensure that the balance is right in terms of sensible reporting scales, there remains a significant value in thinking spatially in terms of how data are produced, managed, disseminated and used. This equally applies to the metadata that are an essential component of a good evidence base.

A final key objective of this report was to identify and comment on data availability and data gaps to move towards informing a better evidence base for future policy development and reporting in public health more generally, as well as to establish potential linkages across the environmental/health interface. Much of these data were focused on hazards such as air pollution, radon and harmful water and it was important to consider other indicators that moved beyond current risk/harm data collection priorities. From a policy perspective, there was also the ongoing issue of the goodness of "spatial fit" between the different data that different agencies collect. This was (and is) not just a problem in comparing point/individual-level data with areal/aggregated data (this is less and less an issue given the development of GISs and other geospatial modelling techniques), but equally recognised the reality of the often fluid nature of spatial boundaries within the health sector and the need to consider something that fits with those and other shifting administrative data collection geographies.

3.3 Audit of Health Data

3.3.1 Health data sets explored

Specific data sets that might begin to fit the criteria of the project, especially those related to a meaningful level of spatial detail (scalar) and comparability across two or more time periods (temporal), were initially identified via the EPA SAFER and HIQA data catalogues. The HIQA metadata were especially useful, with fields listing geographical coverage and frequency of update. In considering data categories, we broadly followed the categories used in the HIQA audit of service-specific, census, regional, collated and survey data in sections 5–9, respectively, of that report (HIQA, 2014). From these two data audits, a number of potentially useful clinical and wider administrative data sets were identified, which were collated under three broad categories:

1. measured data: quantitative data from clinical and other collections;
2. self-reported data: comprehensive national data from the census and other surveys;
3. derived: data sets developed from other data, such as raw census data.

As a second stage, the different data audits, as well as specific listings in other known sources, were examined in depth to identify those data sets that were likely to have good accessibility and ease of use within the constrained 12-month timescale of the project. This meant that clinical and other health service-specific data, especially data that might require data matching in the form of geocoding, were not considered. This applied specifically to data such as hospitalisation data from the (HIPE) system, data on prescribing, potentially available via Health Atlas Ireland, and primary health data on medical card holdings from the Primary Care Reimbursement Service (PCRS) system. For longer term work in the future, such data have considerable potential and this has been noted, specifically in the DASSL report. However, for the purposes of this research, the lack of immediate spatial tagging meant that the data were not considered for the modelling.

Similar constraints applied to survey-based self-reported data. There is a rich and developing set of health survey data in Ireland, some of which have genuine potential for spatial modelling (see Dempsey *et al.*, 2017). Of special interest are the longitudinal data sets such as GUI and TILDA. Annual and less regularly collected surveys, such as the European Union Statistics on Income and Living Conditions (EU-SILC), the Irish Health Survey and others, have less well-developed geographical tagging or regularity of collection, although they remain valuable in terms of profiling. Again, with appropriate spatial tagging, there is the potential to aggregate some of these data in future, especially given that most surveys have a sound “spatial representation” component built into their original sampling design.

3.3.2 Health data chosen for modelling (see also Appendix 1)

Six primary data sets, operating across several different scales of analysis, were identified as appropriate for the modelling. The rationale was based on the following requirements:

- national coverage;
- comparable across more than one time period;
- identifiable as something that acted as either a full or a proxy indicator of health outcomes;
- publicly owned and available (with manageable conditions);
- properly spatially tagged;
- linkable to administrative boundary geographies;
- available at a meaningful geographical scale for statistical analysis.

The core metadata for the specific data sets chosen are provided in Appendix 1 and the data sets are described briefly in the following sections. In addition, some brief illustrations are provided, at different scales, of what the data look like when visualised within a GIS.

Measured: mortality data at intermediate-area scale

These data were derived from official death records, geo-referenced by the National Centre for Geocomputation (NCG) at Maynooth University as part of a HRB-funded project, and cover each year between 2006 and 2011. The geography used, IA, was a new geographical scale, based on a geospatially derived aggregation of EDs, to produce 407 areal units with an average population of around 10,700 in each. For a full discussion see Rigby *et al.* (2017), from which Figure 3.2 is taken.

Self-reported: census health data

These data were available at SA, ED (Figure 3.3) and settlement scales and also aggregatable to IA level for both 2011 and 2016. Data were listed against five categories: very good, good, fair, bad and very bad. The questions were adjusted from a three-point scale (good–fair–bad) in 2006 to a five-point scale for 2011 and 2016, which was also standardised across the UK to allow direct comparison with Northern Ireland.

Self-reported: census disability data

These data were available as a broad count from SA and ED scales and also in a more detailed format, with separate individual disability and impairment categorisations at settlement scales for both 2011 and 2016 (Figure 3.4). The prevalence categories (Q16a–g) include conditions associated with vision, hearing, physical activity, intellect, memory, emotional disturbances and chronic illness (including pain and breathing). Although less commonly made available, there are additional questions in the census (Q17a–d) that ask whether or not any of the above disabilities impaired different levels of everyday function. Although these data were not available at SA level, and we did not use them in terms of the identification of study sites, we were able to submit a data request to the Central Statistics Office (CSO) for the raw data at ED level once we had identified the study sites; these data have not been built into the modelling discussed in Chapter 5 because of time constraints but this may be possible in supplementary work.

Derived: Pobal HP Deprivation Index

This was an index developed by the late Trutz Haase in conjunction with Pobal, a semi-state agency, and was compiled for ED (from 1996 to 2016) and SA (2011 and 2016 only) scales (Figure 3.5). Aggregations above these scales are possible, although the lack of an easy-to-access methodology makes this difficult

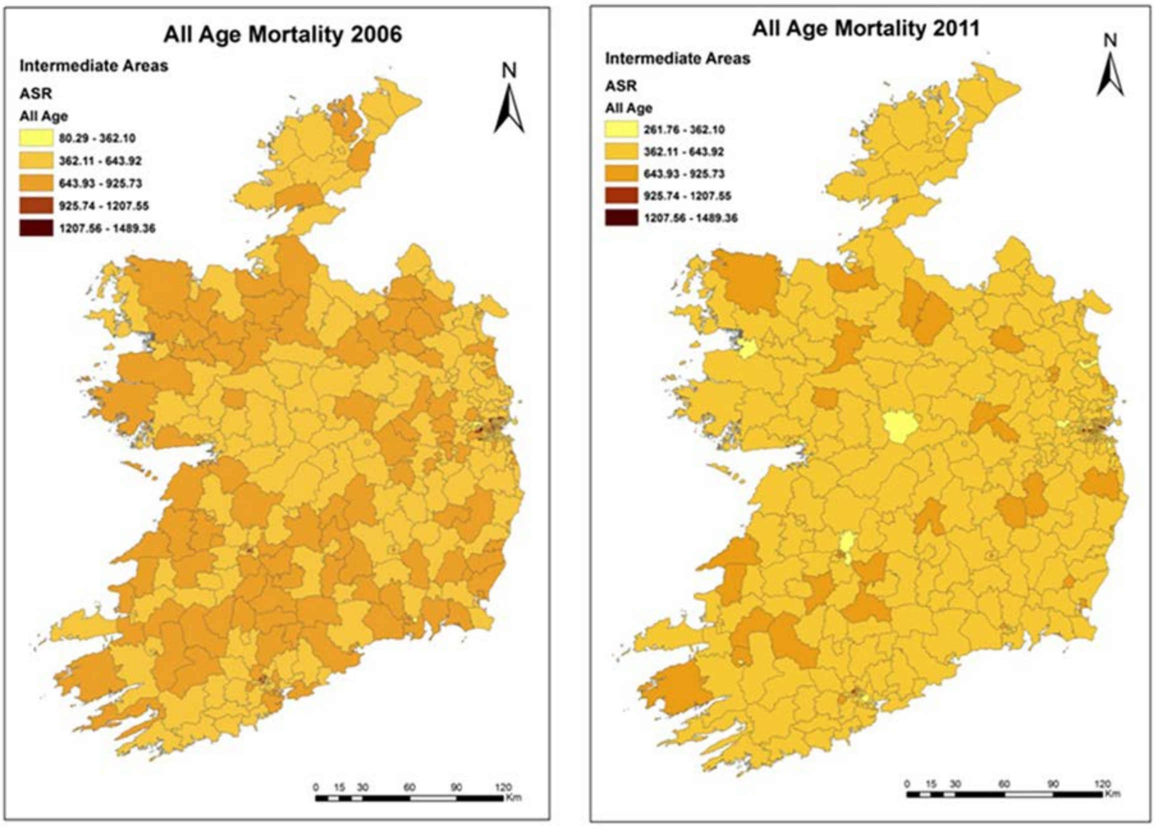

Figure 3.2. Sample: mortality data at IA level for 2006 and 2011. Source: Rigby *et al*. (2017).

Figure 3.3. Sample: self-reported health in Dublin at ED level for 2016. Source: Ordnance Survey Ireland/ CSO, 2018, reproduced under Creative Commons Attribution 4.0 International (CC BY 4.0) licence.

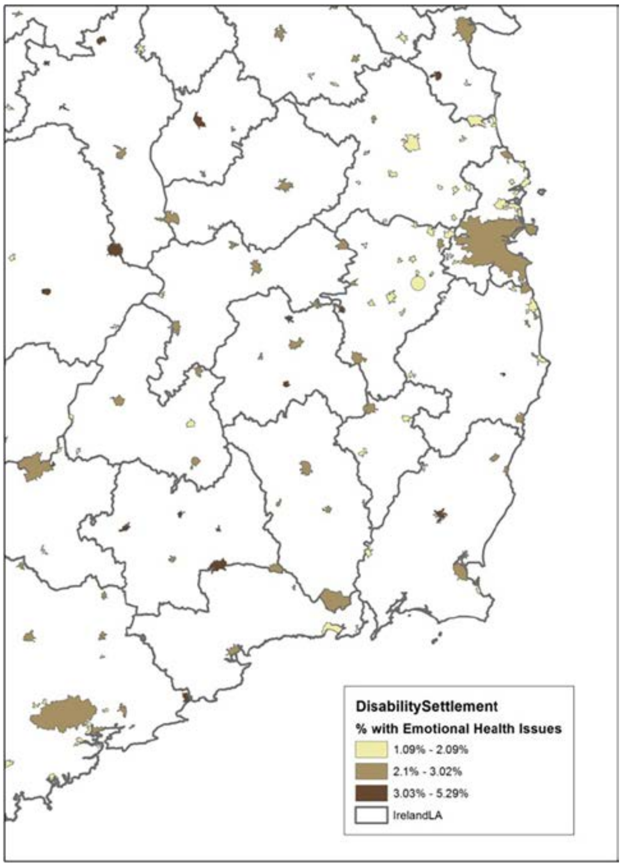

Figure 3.4. Sample: emotional/psychological conditions in Leinster at settlement level for 2011. Source: Ordnance Survey Ireland/CSO, 2018, reproduced under Creative Commons Attribution 4.0 International (CC BY 4.0) licence.

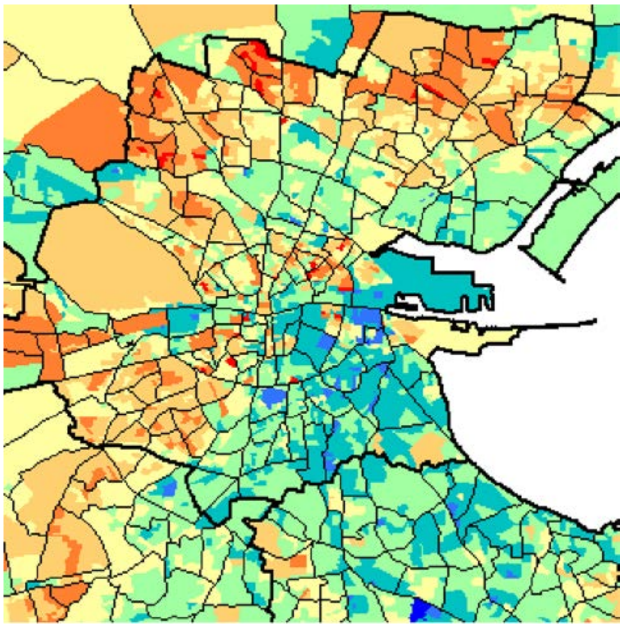

Figure 3.5. Sample: Pobal HP Deprivation Index scores for the Dublin region at ED level for 2011. Sources: Ordnance Survey Ireland/CSO, 2018, reproduced under Creative Commons Attribution 4.0 International (CC BY 4.0) licence, and http://trutzhaase.eu/deprivation-index/the-2016-pobal-hp-deprivation-index-for-small-areas/, under licence through AIRO, Maynooth University.

to reproduce at settlement or IA scale. We were, however, able to work with slightly flawed mean values of the original calculated index at settlement, IA and county scale using a combination of GIS operations (Union and Dissolve).

Derived: Small Area Health Research Unit Deprivation Index

The SAHRU Deprivation Index was a separate index at ED scale based on weighted standardised scores from four census variables (unemployment, low social class, LA housing and no car) and scored by decile. It was also available at SA scale for 2011 and 2016. We have not included a sample map here as the previous example provides a good overview of what a deprivation index map looks like.

Derived: Kavanagh–Foley Index of Wellbeing

The Kavanagh–Foley Index of Wellbeing (KFIW) is a modelled index, based on a weighted relative value of the self-reported health data from the census, available at ED and SA level for 2011 and 2016 only. The weighting is lowest for very good health and highest for very bad health (Foley and Kavanagh, 2014). This is not an established or especially robust indicator, but it does have a solid visual agreement with the expected patterns for deprivation and mortality and was used in the subsequent site selection work.

3.3.3 Metadata

Table 3.1 shows the metadata fields used in the data audit. Specific details for the core data sets are provided in Appendix 1.

Table 3.1. Metadata fields used in the project data audit

Field	Description
Name	The working name for the data set
Type	Category of data set
Code	Coded as measured (M), self-reported (SR) or derived (D)
Method	Way in which data are complied or collected
Question	Short description of text used in collection
Data holder	Owner of the data set
Access status	Nature of availability
Source	Online or other location from which data can be accessed
Form(s)	Technical formats in which data are stored
Years	Timing of data set collection
National	Availability at this geographical scale (Y/N)
Settlement	Availability at this geographical scale (Y/N)
IA	Availability at this geographical scale (Y/N)
ED	Availability at this geographical scale (Y/N)
SA	Availability at this geographical scale (Y/N)
Notes	Additional information about the data set relevant to the project
Status	Usability code, ranging from 1 (fully usable) to 6 (unusable)

The final status field had originally been used for the project; however, on learning more about the other data audits, its use was considered unnecessary, given the relatively limited number of data sets that met the project's criteria. Nonetheless, such a scoring mechanism might potentially be applied in the future, perhaps as an additional geospatial coding for the HIQA and EPA SAFER audits. For example, it was clear that many of the surveys might be coded as either 2 (usable with some processing) or 3 (usable with negotiation) and this would help identify which ones might be prioritised in future in terms of spatial tagging or improved/enhanced access. In addition, it would be helpful to consider other levels of access such as 4 (usable with significant processing and negotiation) and 5 (currently unusable but with potential). Codes in the order of 3 to 5 might also represent the kinds of data that feature in the DASSL report as well. It is also the case that the CSO is currently developing a similar protocol through its new dedicated Research Coordination Unit.

3.4 Future Modelling of Health Data

This chapter has both outlined the identification of health data for use in the GBI Health project and equally provided a wider commentary on the nature and usability of geospatial health data in Ireland today, as well as its potential for future research.

Although the data sets we chose to work with were limited, they acted primarily as a proof of concept to demonstrate the potential of modelling the health benefits of green and blue space and by their nature have an area-based and associational nature. The recent development of substantial audits by the EPA and HIQA was enormously useful, but their is a need to consider more fully the specifically geographical formats of the data sets, which will require some additional work and time. In addition, the coding of the source/access fields of the HIQA data catalogue remains relatively opaque, again not surprising in what the DASSL report identifies as a perceived "closed culture" when it comes to data sharing (Moran, 2016). In addition, the report proposes the development of protocols but also a cross-sectional "Data to Benefits Committee" (Moran, 2016, p. 6), to which this project, for one, would be keen to contribute a geographical perspective to. Positive and clearly articulated suggestions in the DASSL report about the creation of research hubs and safe havens are excellent, but must be balanced against established data cultures and the often hybrid and impenetrable nature of health data collection and dissemination in Ireland.

However, there remains enormous potential based on the data sets identified and what might be done with them. As geographers, we would argue especially that routine spatial tagging at source would be a very valuable starting point to meaningfully improve data dissemination and aggregation, while at the same time safeguarding the data from disclosure. Indeed, in a world in which enormous amounts of personal and private data are being collected, disseminated and shared, there is a parallel process going on that is driven by “Big Data” thinking. Clearly, there are both advantages and constraints of citizen science or citizen-led collections of health data, although these are becoming increasingly common in ongoing work on nature and GBIs (Gidlow *et al*., 2016; Bell *et al*., 2017). As it currently stands, the health data environment in Ireland has a growing mix of publicly and privately collected data, in a mix of quantitative and qualitative formats, that are not being as fully used as they might be. Based on our audit, the identification and coding of a range of data sets in terms of their geospatial potential would be a good starting point. Surveys such as GUI and TILDA have identifiable locations, which can be used to extrapolate associated environmental data in a safe way that respects informed consent but generates useful evidence on health/place relationships and associations, something that is at the heart of this project.

Similarly, individual-level data of all sorts can be relatively easily aggregated, using GISs and other data analytical technologies, to safe higher-level spatial units; for example, sample data on medical card holdings from representative general practices could be aggregated up to either administrative or health service-specific units of a meaningful scale and size such as IAs or PCNs. The issue here seems to be a question of geography as much as ethics/privacy. The next stage of the study identified sample sites/case study areas to match with GBI data to provide some statistical and the associational evidence on how health is shaped by access to such spaces; however, there is much that can be done to develop the availability of and access to meaningful geospatial health data in the next decade.

3.5 Summary

This health data audit ascertained the availability, accessibility and applicability (in terms of the presence or otherwise of spatial references) of health data for GBI and human health modelling. The health data eventually found to be available, accessible and applicable for this project included self-reported health data, mortality data and disability data. Other health and related data accessed using the same criteria (availability, accessibility and applicability) included child development, health service usage and socio-economic deprivation data. Socio-economic deprivation data were used to assess the possible impact of cofounder variables on human health in Ireland. Although the scale at which some of the data were available was unknown (child development and health service usage), socio-economic deprivation data were available at SA and ED levels. Mortality data were available only at IA level because of zero counts at lower levels. Disability data (however, incomplete) were available at settlement level. The IA level was recommended as the basic unit for assessments at smaller scales going forward because it was the only scale, apart from the LA scale, to which all other accessible health data could be aggregated. Data at settlement scale had the weakness of having units that are not necessarily contiguous with units for other scale boundaries. County level is a coarser scale to work at considering that more detailed information at lower levels will facilitate more precise planning. A brief summary of the health data audit is provided in Table 3.2.

The three health data types (i.e. self-reported health, disability and mortality) used were fed into the subsequent sample/case study site selection and statistical modelling process.

Table 3.2. Summary of the health data audit

Health data type	Indicator variables	Ease of accessibility	Availability at different scales
Self-reported health	Percentage of people with self-reported good health (good/very good); percentage of people with self-reported bad health (two-point (bad/very bad) and three point (fair/bad/very bad); KFIW	Available	SA and ED. Aggregated to LA, IA and settlement scales using GIS operations (Union and Dissolve). Sum total of reported counts obtained at LA, IA and settlement scales using GIS operations (Dissolve). Percentage self-reported good health, percentage self-reported bad health and KFIW were calculated for all scales using GIS operations (Field Calculator)
Mortality	Age-standardised rates for people aged less than 75 years	Available but not distributable at finer scales	IA. Data were created originally at IA scale because of the presence of numerous zero values at finer scales. Aggregated only to LA scale using GIS operations (Union and Dissolve). Minimum and maximum values were obtained at LA scale using GIS operations (Dissolve)
Disability	Percentage of people with long-term disability	Available but incomplete. Access to data on specific areas can be made available on request	ST. Aggregated only to IA and LA scales using GIS operations (Union and Dissolve). Minimum and maximum values were obtained at IA and LA scales using GIS operations (Dissolve)
Child development	Self-reported growth curve (GUI and TILDA)	Difficult to access (time limitations)	Not known
Health service usage	Health facility visit; prescription rates	Difficult to access	Not known
Socio-economic deprivation (confounder variable)	SAHRU Deprivation Index; Pobal HP Deprivation Index	Available	SA and ED. Aggregated to LA, IA and ST, settlement scales using GIS operations (Union and Dissolve). Minimum and maximum values were obtained at LA, IA and settlement scales using GIS operations (Dissolve)

ST, settlement.

4 Site Selection and Green/Blue Infrastructure Characterisation

4.1 Introduction

Chapter 3 documented the availability and suitability of health-led data for the development of this GBIHealth project and identified data sets that would drive the work. This chapter describes the next stage of the process and focuses on the final choice of sample/case study sites as well as providing a detailed analysis of the health data chosen for inclusion. This chapter will also detail the ways in which the data were analysed using GIS and spatial statistics, to identify a validated set of study area locations that contained usable measures of good and poor health. In particular, although some preliminary statistical data analysis was used, the core method in the initial stages of site identification used spatial clustering algorithms available within GISs; these are explained more fully in section 4.4 below. The choice of final sites was also informed by consultation with the project's policy partner, EMRA. The final study area locations were chosen to continue the project into its final two WPs, WP3, environmental characterisation, and WP4, statistical modelling. Although the original project plan linked the data audit and choice of sample/case study sites together, the overlap with the environmental characterisation meant that it made sense to discuss the two core data elements, health and GBI, in tandem. Section 4.5 of this chapter lists the chosen sample and case study sites, with an inventory of all of the data sets that informed the final statistical modelling work, which is documented in Chapter 5.

4.2 Spatial Cluster Analysis

The sample/case study site selection process involved an initial geodatabase creation to ensure that data not found at higher-level scales were recalculated at those scales using GIS operations (Union and Dissolve; see Table 3.2). After the geodatabase creation, a spatial cluster analysis [Anselin Local Moran's I (ALMI) statistics algorithm] was conducted to identify clusters of good and poor health at each scale. This algorithm identified spatial clusters of good health and bad health across the different health indicator variables. It classifies all areas into either low–low (LL), that is, clusters with poor health outcomes, high–high (HH), that is, clusters with good health outcomes, low–high (LH), that is, outliers of poor health within areas of good health, and high–low (HL), that is, outliers of good health within areas of poor health. The final category, forming a significant subset on its own and coded as insignificant, included areas with no statistically significant clusters. Spatial cluster analysis was chosen above other data-clustering algorithms because of its capacity to reveal change in health cluster status over time.

Spatial cluster analysis provided an initial list of good and bad health clusters; from this, we selected the sample sites for statistical modelling. Although there may be considerable value in exploring the LH and HL clusters, this was not possible in the time available. The sample sites were arrived at through a stepwise process. The first step was a data-matching process, to ensure consistency between and across the different health indicators. Data matching ensured that places with good self-reported health also had low mortality and disability rates. On the other hand, places with poor self-reported health were checked to ensure that they also had high mortality and disability rates. Second, the frequency of appearance of clusters was tracked across all health indicators and scales of assessment. The places chosen as initial sample sites for the statistical modelling tasks were places that appeared more frequently across all health indicators and within the different scales of assessment. These processes are described in Figure 4.1.

4.3 Identifying Sample/Case Study Site Locations

4.3.1 Data used

Section 3.3.2 and Appendix 1 list the core data sets used as health indicators in this study. These were available at a range of scales and time periods and there were additional "winnowing" processes before the data used for the cluster modelling were identified.

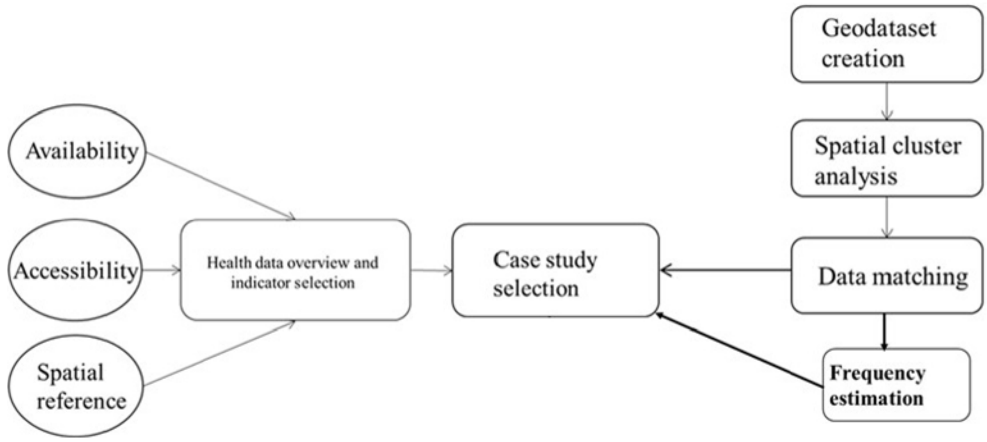

Figure 4.1. A description of the health audit and case study selection WPs.

As noted in section 3.3.2, two different measures of deprivation, the Pobal HP Deprivation Index and the SAHRU Deprivation Index, were identified as effective derived measures of health. One of the wider aspects of the study, however, was to also identify possible relationships in terms of inequality, to add an element of critical analysis in the final modelling. As a result, the deprivation data were excluded from the stage 2 spatial clustering, in part because of autocorrelation difficulties, and were reintroduced at the final statistical modelling stage, documented in Chapter 5.

The data sets used in the cluster analysis are listed in Table 4.1. Although the bulk of the data were for the periods 2011 and 2016, we also included some data from 2006, including census data from that period, as well as mortality data, which were available only for the period 2006–2011. Although ongoing work by the Centre for Health Geoinformatics (CHG) in Maynooth has seen these data updated for the years following 2011 (up to 2014), this was not completed during the timescale of the project. Nonetheless, this data set with direct health outcomes year-on-year for an interesting scale, with additional details on cause of death, is an immensely valuable and under-utilised data set that deserves wider support. The remaining data used for site selection were census based and publicly available at a range of scales.

Although the KFIW, as noted previously, was a very broad indexed score, it was calculated at SA level and as a result could be aggregated up to higher-level scales within a GIS. The disability data, based on Q16 and Q17 in the census, remain an underused data set, as they are currently not made available at ED or SA level for confidentiality reasons. Although they are not likely to ever be made available at SA level, data requests to the CSO for ED-level data for the sample/case study sites for 2011 and 2016 were prepared for the project and these data will be modelled in follow-up work. The overall percentage of people declaring that they had a disability in Q16 of the census was the main measure that we used; we incorporated individuals who ticked *any* of the seven categories listed on the form. Once all of the above data sets were explored, sufficient data had been gathered to determine the initial list of potential sample/study area sites.

It is important to state that, despite our best efforts at producing a standardised listing for two different time periods for all of the core data sets, we were not completely successful in this attempt. As noted above in the case of the mortality data, it would have been preferable to have had 2016 data available but these had not yet been developed. When there was a difference in the smaller-level aggregations, these were almost entirely at SA level, where boundary changes associated with a re-engineering of the OS (Ordinance Survey Ireland) boundary layers linked to Global Positioning System (GPS) updating caused around an 8% mismatch. However, given that the final modelling was carried out at the more aggregated IA scale (see Chapter 5), this was less of an issue than it might have been. This will be discussed further in section 4.6 in terms of alignment issues between the health and the GBI data.

Table 4.1. Health data used in site selection

Name/type	Scale	Dates	Units, *n*	Content	Source
Mortality	IA, LA	2006–2011	IA: 407; LA: 34	Age-standardised all-cause mortality in those aged less than 75 years (premature); four main causes (stroke, cancer, heart, respiratory)	CHG-MU
Self-reported health	SA, ED, ST, IA, LA	2011 and 2016	SA: 18,488; ED: 3409; ST: 811; IA: 407; LA: 34 (2011) SA: 18,641; ED: 3126; ST: 811; IA: 407; LA: 31 (2016)	Five-point scale from very good to very bad	CSO
Disability	ST, IA, LA	2011 and 2016	ST: 197; IA: 174; LA: 13 (2011) ST: 197; IA: 191; LA: 14 (2016)	Overall percentage reporting a disability; more detailed categories at ST scale only	CSO
KFIW	SA, ED, ST, IA, LA	2011 and 2016	SA: 18,488; ED: 3409; ST: 811; IA: 407; LA: 34 (2011) SA: 18,641; ED: 3126; ST: 811; IA: 407; LA: 31 (2016)	Weighted score derived from self-reported health	CSO-Geography at MU

MU, Maynooth University; ST, settlement.

4.4 Cluster Analysis

4.4.1 Why use clustering approaches?

There are a number of ways to identify clusters of data. For this project, the rationale for following a clustering approach was to identify patterns within and across the data sets, to help us identify “places of interest”. This process also enabled the meaningful identification of areas that had a distinct health indicator profile and outcomes. The role of cluster analysis broadly was to use the data to pick up similarities and dissimilarities in the data, with a particular focus on identifying areas with clusters of poor health indicators and, its corollary, areas with clusters of good health indicators. This was also important to account for statistical consistency in relation to the follow-up spatial modelling in Chapter 5, which produced the core results associated with the study.

4.4.2 Spatial clustering

Given that the focus of our work was strongly geospatial, we chose spatial clustering over data clustering. This helped identify spatial clusters of good and poor health over the whole of Ireland. Spatial cluster analysis was chosen above other data-clustering algorithms because of its capability to reveal change in health cluster status over time. These spacial cluster analysis algorithms identified specifically “spatial clusters” using the contiguity of the areas at different scales as the key starting point. Available spatial cluster analysis algorithms explored included cluster and outlier analysis (ALMI), grouping analysis, hot spot analysis (Getis–Ord Gi*), optimised hot spot analysis and similarity search.

We tested these different algorithms in turn to identify the optimal choice for use within this study. In the case of the second to fifth options, we identified a number of constraints, some involving the identification of full temporal data (grouping analysis) and others requiring fuller knowledge of optimal kernel distances (hot spot analysis), which made them slightly more difficult to operationalise against the available data. Because of these constraints, the ALMI was deemed the best tool, precisely because it produced the best visualisation of the results and one that might be most comprehensible to a non-expert audience. Essentially, AMLI assigns an indexing and weighted z-value score to each polygon and then examines all of the surrounding polygon scores in sequence to identify hot spots, cold spots and outliers. It also controlled for autocorrelation, a type of “contamination effect” in which the value for one area affected others nearby and skewed the statistical outputs.

In terms of how these cluster classifications emerged from the modelling, the majority of locations were coded as neutral. Hot spots were coded (depending on the variable being used and its data range) as being either clusters of high values (coded as HH) or clusters

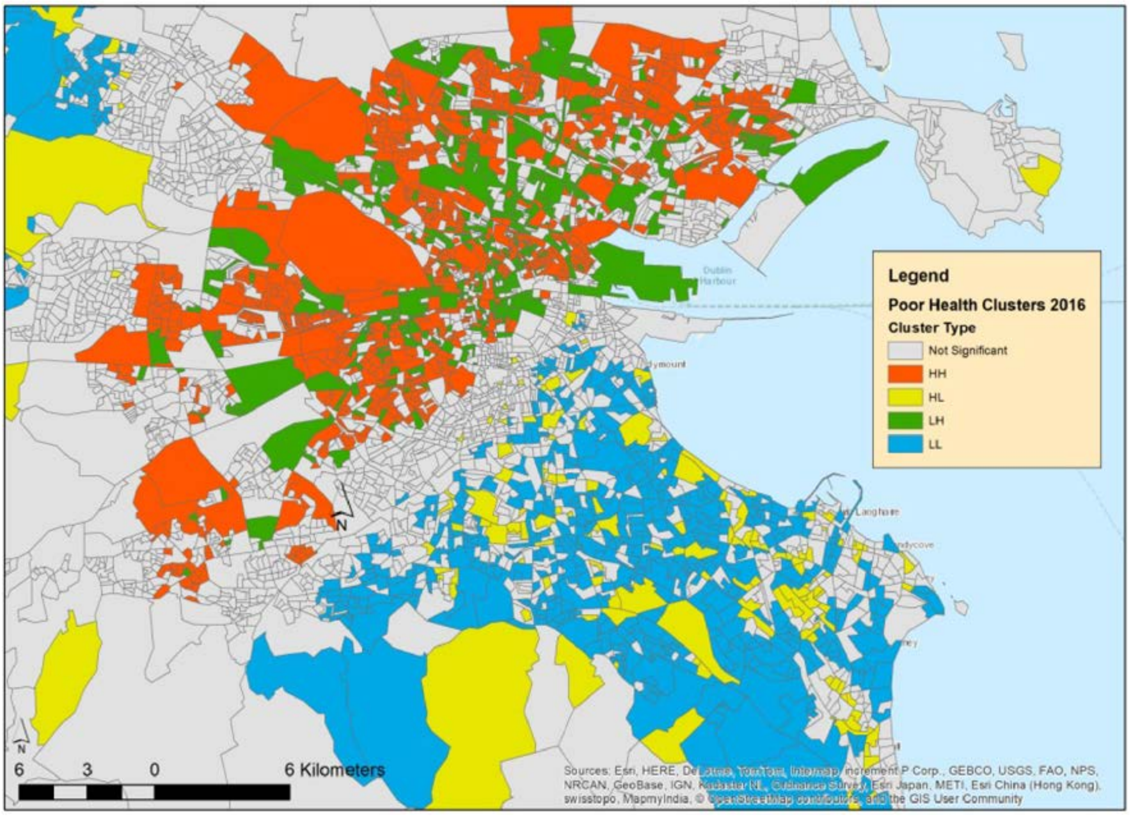

Figure 4.2. Sample spatial clustering results: poor health in Dublin at SA level for 2016. Source: Ordnance Survey Ireland/Central Statistics Office, 2018, reproduced under Creative Commons Attribution 4.0 International (CC BY 4.0) licence.

of low values (coded as LL). Outliers were coded in two forms, as HL (outliers of high value within an area of low values) or LH (outliers of low value within an area of high values). For example, considering the percentage of people in poor or very poor health, the ALMI method identified clusters of areas of deprivation and affluence (as HH and LL respectively), with HL identifying deprived areas within more generally affluent areas and LH identifying affluent outliers within generally deprived areas. Figure 4.2 provides a representative example of the clustering of poor health scores in 2016 at SA level for the Dublin area. It should be noted that, the more detailed the geography, the more areas will be identified, but it does give a good sense of a complex pattern that still confirms the established north-east/south-west divide. The yellow areas represent pockets of poor health in the more affluent Southside, whereas the green areas represent the corollary (pockets of good health in generally deprived areas) on the Northside.

Spatial clustering stage 1: initial data

The next stage of the clustering essentially used all of the individual data sets listed in Table 4.1 and modelled each in turn using the ALMI methodology. This produced a five-class scale for all health indicators for each of the different scales (county, settlement, IA, ED and SA) for which individual data were available. This produced a very complex set of results, which are described in the following sections. Although valuable in identifying named HH, LL, HL and LH clusters across multiple scales, the results were unwieldy at lower scales, especially at the ED and SA levels, for which the results consisted of very lengthy lists. At IA and settlement level the results were more manageable, with the former the more reliable scale. In addition, the areas that emerged were quite heterogeneous across the different health indicators, with the mortality, self-reported health and disability clusters being the most reliable. The KFIW data clusters tended to be confirmatory of the self-reported health scores as they were very closely linked. Although we also ran the cluster algorithm for deprivation data, we did not include this in the next ranking stage of the process. One other important thing to note was that not all of the scores followed the same range. Whereas specific “poor” health indicators needed to be interpreted correctly, that is, high scores represented poorer health, the reverse applied for areas with “good” health scores. In addition, the Pobal HP Deprivation Index used an inverse range so that the most deprived areas had a high negative score whereas the most affluent areas had a high positive score. It should be noted, especially at IA and settlement scales, that the Pobal HP Deprivation Index scores were higher in clusters with bad or poor health outcomes and lower in clusters with good health outcomes. These were all controlled for in the next stage in the process.

Spatial clustering stage 2: data matching and frequency establishment

The initial set of sample sites selected for statistical modelling were those that appeared most frequently across all health indicators and within the different scales of assessments. Sample site selection was initially restricted to the three larger scales (county, IA and settlement) to give room for comparison of the level of consistency in the choices. Many of the clusters revealed by the ALMI statistics were found to be within the same counties, IAs and settlements. Sample clusters of good and bad health across different scales were diverse and quite representative. They comprised both places with high, low and no proportion of GBIs and places with high and low socio-economic affluence and deprivation levels. These are listed more fully in Tables 4.2–4.7. They also provide an indication that GBI and confounder variables (e.g. socio-economic affluence and deprivation levels) are both important factors that determine health outcomes in Ireland. They should therefore go hand in hand in GBI and health modelling studies. This is a major advantage of a health-led approach to GBI and health modelling. It first identifies clusters of good and bad health and then brings out the spatial patterns of health outcomes, without giving priority to areas where GBIs are located or where data on GBI are available.

Table 4.2. Clusters of good health at county scale (2016)

County	Green proportion index	Blue proportion index	SAHRU Deprivation Index score (mean)	Pobal HP Deprivation Index score (mean)
Fingal	0.8	0.0058	6.65	14.87
Dún Laoghaire–Rathdown	0.45	0.063	3.36	18.72
Kildare County	0.89	0.056	4.92	12.94
Kilkenny County	0.97	0.0098	3.2	12.9
Meath County	0.96	0.012	4.91	9.52
Cork County	0.9	0.078	2.81	15.98

Table 4.3. Clusters of bad health at county scale (2016)

County	Green proportion index	Blue proportion index	SAHRU Deprivation Index score (mean)	Pobal HP Deprivation Index score (mean)
Dublin City	0.15	0.014	9.07	22.51
South Dublin	0.58	0.075	8	13.92
Fingal	0.8	0.0058	6.65	14.87
Dún Laoghaire–Rathdown	0.45	0.063	3.36	18.72
Kildare County	0.89	0.056	4.92	12.94
Kilkenny County	0.97	0.0098	3.2	12.9
Laois County	0.94	0.04	3.5	12.02
Waterford City	0.48	0.08	8.02	7.9
Galway City	0.47	0.06	3.14	12.48

Table 4.4. Clusters of good health at IA scale (2011)

IA	Green proportion index	Blue proportion index	SAHRU Deprivation Index score (mean)	Pobal HP Deprivation Index score (mean)
Ballysimon	0.82	0.0065	–0.99	8.51
Blakestown NW	0.1	0	–0.073	3.44
Dunshaughlin Kilcloon	0.99	0	1.36	7.74
Kildare NE	0.95	0.0027	–0.63	13.37
Lucan Central	0.01	0	–0.52	6.69
Meath S	0.97	0.0012	–0.16	8.21
Wicklow E Central	0.71	0.27	0.77	8.25
Wicklow E	0.82	0.07	0.11	10.99

Table 4.5. Clusters of bad health at IA scale (2011)

IA	Green proportion index	Blue proportion index	SAHRU Deprivation Index score (mean)	Pobal HP Deprivation Index score (mean)
Cabra N	0.052	0	4.39	5.58
Cabra S	0.07	0	3.54	–3.02
Cork Urban NW	0.16	0	9.09	–6.14
Crumlin E	0	0	4.56	–8.76
Fair Hill Farranferris	0.14	0	6.2	–8.76
Kylemore Kilmainham W	0.01	0	5.17	–4.28
Limerick Urban E	0.00014	0	5.7	–3.75
Limerick Urban NE	0.34	0.1	11.03	2.59
Limerick Urban NW	0.22	0.014	7.71	0.34
Limerick Urban S	0.14	0.08	10.29	–7.27
Ushers S	0	0	7.82	–1.42

Table 4.6. Clusters of good health at settlement scale (2006)

Settlement	Green proportion index	Blue proportion index	SAHRU Deprivation Index score (mean)	Pobal HP Deprivation Index score (mean)
Ashbourne	0.16	0	0.2	–0.38
Ballinspittle	0.1	0	0.3	–2.05
Ballygarvan	1	0	1.1	–5.88
Carrignavar	1	0	–0.88	1.93
Carrigtwohill	0.11	0	–0.22	6.85
Cloughduv	0.39	0	–0.37	3.59
Dunboyne	0.16	0	–1.16	6.48
Dunderrow	1	0	–1.09	7.98
Dunshaughlin	0.28	0	–1.24	4.89
Farran	1	0	–1.83	7.01
Glenville	0.55	0	–1.26	4.98
Innishannon	0.56	0	–1.67	8.64
Killumney	0.78	0	–2.02	9.19
Rathard	1	0	–2.23	9.63
Ratoath	0.22	0	–1.19	4.89
Riverstick	0.27	0	–1.26	4.28
Whitechurch	0.45	0	–0.88	1.93

Table 4.7. Clusters of poor health at settlement scale (2006)

Settlement	Green proportion index	Blue proportion index	SAHRU Deprivation Index score (mean)	Pobal HP Deprivation Index score (mean)
An Clochán Liath	0.42	0.15	1.27	–9.52
Ballaghaderreen	0.35	0.05	3.76	–12.93
Bellanagare	1	0	–0.048	–7.9
Boyle Legal Town and its Environs	0.65	0	2.94	–11.26
Castlerea	0.46	0.0027	2.74	–7.56
Convoy	0.49	0	1.5	–9.85
Gob An Choire	0.57	0.093	1.2	–12.02
Keel–Dooagh	0.53	0.13	1.34	–8.16
Kilrush Legal Town and its Environs	0.65	0.04	3.37	–10.11
Loch an Iúir	0.72	0.28	1.48	–10.05
Loughglinn	0.92	0.076	1.59	–11.28
Mín Lárach	0.79	0.21	–0.12	1.83

4.5 Sample Site/Case Study Selection

The modelling approach undertaken by this study was two-way, namely a multi-scale and a single-scale modelling approach. Both modelling approaches were necessary; the multi-scale modelling approach first helps to identify an appropriate scale to model relationships between GBI and health and wider relationships between socio-economic affluence/deprivation and health. The choice of scale that seemed most sensitive to GBI and health relationships and socio-economic affluence/deprivation and health relationships was based on this multi-scale modelling approach (using the areas identified across Tables 4.2–4.7). The choice of scale from the multi-scale modelling in turn informed a more detailed single-scale assessment, which formed the basis for identifying further GBI and health associations, as well as GBI and health planning interventions (using the areas listed in Table 4.8). The multi-scale statistical modelling examined the strength of associations between GBI and health and between socio-economic affluence/deprivation and health (as confounder variables) using a coefficient of determination (R^2 value computation), across three basic scales, namely county, IA and settlement scales. There was, however, no ranking of impacts of GBI against socio-economic affluence/deprivation. As our work has emerged as primarily a proof-of-concept study, subsequent research may be able to establish such a ranking.

Associations were tested at multi-scale and single-scale levels using the coefficient of determination (R^2 values), which measured associations between the presence of GBI and good health, as well as associations between socio-economic affluence and good health. Conversely, associations between the absence of GBI and poor health, as well as associations between socio-economic deprivation and bad health, were also examined. Reverse associations such as those between the presence of GBI and poor health, the absence of GBI and good health, socio-economic affluence and bad health and socio-economic deprivation and good health were also considered within the analysis.

For the multi-scale and single-scale assessments, the independent indicator variables employed to test the impact of GBI on different health indicators were the green proportion index or green infrastructure proportion index (GPI) and the blue proportion index or blue infrastructure proportion index (BPI). The GPI was the ratio of green areas or spaces (e.g. forests, arable lands, pastures, gardens, sports and recreational fields, playing spaces, green urban areas, vegetation on sands, dunes and beaches) to the overall area within a sample unit of space (either county, IA, settlement, ED or SA). The BPI was the ratio of blue areas or spaces (e.g. wetlands, marshes, rivers, lakes, streams, seas) to the overall area within a sample unit of space. The GPI and BPI were chosen as indicators because they had the potential to establish the proportion of GBI needed for health improvement. The amount of GBI needed to ensure health improvement across different scales is, however, yet to be investigated at this stage of reporting. This can, however, be carried out using regression and goal-seeking modelling post study.

Calculation of the GPI and BPI for the multi-scale modelling at county, IA and settlement scales was carried out using CORINE (CO-ordination of infoRmatIon on the enviroNmEnt) land cover data for 2006 and 2012 (with a spatial resolution of 30 m) (European Environment Agency, 2007). At county, IA and, settlement scale level, CORINE data for 2006 were used for modelling of health outcomes for 2006. We used CORINE data for 2012 for modelling of health outcomes for 2011. We assumed that there were no significant differences in the data between 2011 and 2012. We also used CORINE data for 2012 for modelling the health outcomes of 2016 because there were no new CORINE data for the 2016 assessment year. We therefore adopted the most recent data in relation to the 2016 assessment year, which were the CORINE data for 2012. CORINE data were preferred for the multi-scale modelling because of the wider coverage over the whole of Ireland, despite the poor spatial resolution of 30 m.

The calculation of the GPI and the BPI for the more detailed single-scale modelling for case study sites was completed using higher spatial resolution Urban Atlas (UA) land cover data (spatial resolution of 2.5 m) (https://data.europa.eu/euodp/en/data/dataset/data_urban-atlas). Whereas the sample sites for the multi-scale modelling were chosen based on a wider coverage over the whole of Ireland, in order to prevent bias in the choice of scale (using freely available and wider coverage CORINE data), sample sites for the more detailed single-scale modelling were chosen based on some additional specific spatial criteria. This included rural and urban diversity, coastal and inner-city variation and coincidence with EMRA priority sites (considering that EMRA is an internal partner on this project). The final criteria and chosen case study sites for the more detailed single-scale modelling at IA level are listed in Table 4.8.

Whereas green infrastructure was more fully defined and specified within the UA land cover data, blue infrastructure was better defined and specified within the CORINE land cover data. For example, marshes, intertidal flats and wetlands were separate (individual blue infrastructure) land cover classes within the CORINE land cover data. These three (blue infrastructure) land cover classes (i.e. marshes, intertidal flats and wetlands) were merged into the agricultural, semi-natural areas and wetland class of the UA land cover data. Even though both CORINE and UA land cover data had several classes of urban land use with different densities of vegetation, UA land cover data had more classes. The spatial accuracy and acceptability of the use of green infrastructure information from UA land cover data are also likely to be better than those from CORINE land cover data because of the coarser spatial resolution of CORINE land cover data. Consequently, for the multi-scale modelling, we adopted only one GPI value for green infrastructure information from CORINE land cover data. However, because of the higher spatial resolution and better acceptability of green infrastructure information from UA land cover data, we adopted three GPI values (GPI-1, GPI-2 and GPI-3) for the more detailed single-scale modelling, to promote a more

Table 4.8. Selected case study sites for single-scale modelling at IA level

IA name	EMRA	Urban	Rural	Coastal	Inner city
Dunshaughlin Kilcloon	Y	Y		Y	
Lucan Central	Y	Y			Y
Wicklow E	Y		Y	Y	
Blakestown NW	Y	Y			Y
Ballysimon	N	Y		Y	
Cabra S	Y	Y			Y
Crumlin E	Y	Y			Y
Kylemore Kilmainham W	Y	Y			Y
Limerick Urban NW	N	Y		Y	
Cork Urban NW	N	Y		Y	

robust analysis of the impact of green infrastructure on health. The first index, GPI-1, was computed using the upper estimate limit for vegetation obtained from the first two UA urban land cover data categories, namely 50% up (listed in Table 4.9). The other two indices, GPI-2 and GPI-3, were obtained from the other upper limits of vegetation coverage for the third class (up to 70%) and the final two classes (up to 90%) of urban land use, respectively.

The upper and lower limits of the vegetation coverage of urban land use classes were not used to obtain more GPI values for the multi-scale modelling because CORINE land cover data had coarse spatial resolution; using multiple GPIs would have been more problematic in the multi-scale modelling.

The dependent health indicator variables chosen in this study are shown in Table 4.10. There are four indicator variables for self-reported health. They include the percentage of people with self-reported good health, the percentage of people with self-reported bad health (two-point scale), the percentage of people with self-reported bad health (three-point scale) and the KFIW. The percentage of people with self-reported good health is the proportion of those with self-reported good health and self-reported very good health among the Irish population. The percentage of people with self-reported bad health (two-point scale) is the proportion of people with self-reported bad health and self-reported very bad health among the Irish population. The percentage of people with self-reported bad health (three-point scale) is an indicator of poor health that adds self-reported fair health to the computation of the percentage with self-reported bad health. This is because the inclusion of self-reported fair health was identified as a possible explanation for the disparity between Irish results and results for the rest of the British Isles (Foley and Kavanagh, 2014). The KFIW was an indicator of poor

Table 4.9. Upper and lower limits of vegetation coverage within the urban land use classes of UA land cover data

Urban land use classes	Lower limit of vegetation coverage (%)	Upper limit of vegetation coverage (%)
Continuous urban fabric (Sealing Layer (SL): >80%)	20	20
Discontinuous dense urban fabric (SL: 50–80%)	20	50
Discontinuous medium density urban fabric (SL: 30–50%)	50	70
Discontinuous low density urban fabric (SL: 10–30%)	70	90
Discontinuous very low density urban fabric (SL: <10%)	90	90
Isolated structures	0	0
Industrial, commercial, public, military and private units	0	0
Other roads and associated land	0	0
Railways and associated land	0	0
Mineral extraction and dump sites	0	0
Construction sites	0	0

Table 4.10. Independent and dependent variables in the statistical modelling task

Independent variable – X (GBI indicators)	Dependent variable – Y (health indicators)	Confounder variables (demographic, socio-economic and locational variables)
GPI – green area/overall area BPI – blue area/overall area	Self-reported health – percentage of people with self-reported good health (very good + good health); percentage of people with self-reported bad health (two-point scale – very bad + bad health; three-point scale – fair + very bad + bad health); KFIW Disability data – percentage of people with long-term disability conditions Mortality data – age-standardised mortality rate of people under the life expectancy age (ASR U75)	Socio-economic deprivation – Pobal HP Deprivation Index SAHRU Deprivation Index

health that weighted bad health over good health based on local expert knowledge of Irish data.

Several self-reported indicator variables were deployed to improve the robustness of the analysis. Associations between GBI availability and percentage with self-reported bad health (two-point scale), as well as between socio-economic deprivation indices (SAHRU and Pobal HP) and percentage with self-reported health (two-point scale) may be either strengthened or weakened by the introduction of self-reported fair health and expert weightings to the computation of poor health indicators. The introduction of self-reported fair health to the computation of poor health indicators can be done by deploying the three-point scale for the percentage with self-reported bad health. The inclusion of expert weightings to the computation of poor health indicators can be done using the KFIW. The equation for the KFIW is illustrated below:

$$\begin{aligned}\text{KFIW} = {} & (\text{\% with very good health} \times 1) \\ & + (\text{\% with good health} \times 2) \\ & + (\text{\% with fair health} \times 3) \\ & + (\text{\% with bad health} \times 4) \\ & + (\text{\% with very bad health} \times 5) \qquad (4.)\end{aligned}$$

The confounder socio-economic affluence/deprivation indicator variables for this study were the SAHRU Deprivation Index and the Pobal HP Deprivation Index. For the multi-scale modelling at county, IA and settlement levels, minimum and maximum SAHRU and Pobal HP Deprivation Index values obtained from GIS operations (Union and Dissolve) were used for modelling the statistical relationships and are reported partially in Chapter 5.

4.6 GBI Data Characterisation

4.6.1 Typical data: natural environments and green/blue space

Although the focus up to now has been on the health-led data, there were additional and related audits that related to GBI, but which had some overlaps. The EPA SAFER initiative is one example (EPA, 2014) in which health data sets were a small subset of a much fuller listing of environmental data sets that incorporated elements of GBI. Some of these data could certainly be classified as environmental health data, although it should be noted that there was a strong health risk component to these measures. It is important not to discount the role of health-reducing as well as health-enhancing elements in measuring the "healthiness" of any area or GBI element. Indeed, one interesting way forward for future modelling might be the development of a "weighted health score" for an area, balancing out risk/gain, although this is beyond the scope of the current project. In addition, a recent EPA-funded synthesis report, *Health Benefits from Biodiversity and Green Infrastructure* (Carlin *et al*., 2014), included a section listing the potential of geocoded data in future research. Table 4.1 from that document listed some of the key GBI data sets, which have also informed the thinking behind this project more broadly.

Both EPA reports considered the types of data typically used in what might be described in broad terms as "healthy nature" research and there are a number of recent reviews that clarified the approaches and data used in that work (Frumkin, 2003; Lachowycz and Jones, 2013; van den Bosch and Ode Sang, 2017). Although there was a strong presence of environmental psychology in this research, it was also driven by more outdoors and spatially based research that incorporated the use of survey, area-based and qualitative approaches. Again, it is important to point out that these were GBI led rather than health led, but focused strongly on the inter-relationship between them and did emphasise the collection of health data. The health data used in those studies had a strong emphasis on individual or small sample data. Although area-based health data were less commonly used, these data have become more popular, especially in blue-space research (Wheeler *et al*., 2012). When surveys have been used, the locations of respondents have been linked against quite broad "situated geographies", that is, the location of individuals has been used to drill down into associated aggregate data for that same location. This latter approach represents an interesting route, and ongoing research by the Economic and Social Research Institute, based on TILDA data, has shown that there is potential for such work, although one might add that there is still plenty of scope for parallel neighbourhood and area-based modelling (Dempsey *et al*., 2017).

4.6.2 GBI mini audit

In looking in more detail at identifying relevant and usable GBI data for the project, the initial intent of the research was to try and characterise the environments of the case study areas down to street level and map the GBI elements identified as potentially contributing to improved health outcomes. However, these fine-scale (street-level resolution) land cover data, to capture the GBI elements influencing health, were not universally present throughout Ireland and as a result there was no guarantee that such data would be available for all identified case study sites. In the following sections some data sets of interest are described; the availability and suitability for modelling of each was noted, with the first two identified as the examples to be used in the statistical modelling described in Chapter 5. At the heart of this mini-audit were the same elements that mattered for the health data: scale, availability and comparability.

CORINE

The CORINE data set is a standardised European land use classification based on satellite imagery. It is produced at regular intervals and for the purposes of this project was timely in that data for 2006 and 2012 were available, which matched some of the timings of the health data. The scheme applies a complex typology of hierarchically coded land uses, running down to three levels. A typical classification is shown in Appendix 2, which showed that there are five broad categories of land use (artificial, agricultural, forest and semi-natural, wetlands and water bodies). There are two further levels of sub-classification, which add detail at each level. For the purposes of this research, for example, three-level codes such as 141, Green urban areas, and 512, Water bodies, are examples of categories of special interest. As a national data set, its coverage included all of the case study sites. This data set was used in the multi-scale modelling.

Urban Atlas

This is a data set closely linked to the CORINE data set but with some additional significant detail within a narrower geography. Rather than cover whole countries, it covers broad urban regions and, in the case of Ireland, this includes the Dublin, Limerick and Cork areas within which the sample/case study sites sat. It also groups the CORINE categories in a slightly different format, although the codes are broadly similar. In the case of UA, there are grouped codes for green urban areas (14100), forests (30000) and water bodies (50000). In addition, the data are collected and digitised at a finer spatial resolution and provide a sharper geographical delineation than the CORINE data. These data were used in the single-scale modelling.

Normalised Difference Vegetation Index

The NDVI has been a widely used indicator in this type of research. Typically a measure of plant greenness, it is calculated on the basis of the difference between the red and the near-red bands from a remotely sensed image. It is especially suited to the identification and mapping of the tree and shrub canopy and has been used as an indicator in green-space modelling especially. Although it can identify blue space, the data quality is poorer for this type of land use and, as a result, it does not have the full scope and range needed for our modelling. In addition, it requires a significant amount of additional processing and the time taken to develop this partial data set was not considered an efficient use of project management.

i-Tree Canopy

This is a specific modelling tool that uses a sampling approach from satellite imagery to identify tree canopy cover. These data have been used effectively in green-space modelling in Ireland, with some of the project team using the tool to generate tree canopy cover for Irish case studies (Mills *et al*., 2015). In effect, the software cookie cuts a bounded geographical area through Google Earth imagery and, using a sampling frame of points, identifies and classifies land use, specifically in eight categories: grass, shrubs, trees, buildings, roads, other impervious, water and other. Although there is considerable potential for this tool, the sampling does take a long time to generate and the focus is also primarily on urban green space, albeit with some capacity to identify blue space. Because of the sampling approach and the range of areas involved, this data set was excluded for time reasons, although, as noted, it has considerable potential. In addition, other associated research by the team members also established, using a separate tree canopy approach, a strong relationship between low levels of tree canopy cover and deprivation in Dublin (Brennan *et al.*, 2017).

Satellite imagery

Finally, there has been a steady development in the amount, quality and availability of satellite imagery over the past decade. As documented in the EPA SAFER survey (EPA, 2014), data of varying spatial resolution from the IKONOS, Landsat, QuickBird and SPOT satellites are now available for Ireland. Although these data are of high quality, they are not free and require significant additional work around access and processing. Again, the timescale and funding of the project meant that we were not in a position to use these data sets, although they would be valuable for longer term work in this area. Finally, the development through the Copernicus programme of access to high-quality and regularly collected Sentinel satellite data offers a valuable future route for this kind of work, although again it was too late for this project.

4.7 Identified GBI Data for Study

Based on the above exploration and identification of usable and available GBI data sets that would help us characterise the GBI for our research, the final choice of data sets for use in the GBI part of the model were the CORINE and UA data sets. These data sets provided full overlapping spatial coverage with the study sites and the data sets that provided the health indicators. They were also extractable against any unit of analysis that we required, something that it would be harder to do with more partial data sets. Although it was our intent to try and develop some new remotely sensed data sets, this was not possible within the time/funding constraints of our study. However, in the case of several of these remotely sensed data sets, there is research evidence as to their potential value in longer term projects in which there would be time for their development within sample or representative studies of individual locations. The potential of the new Sentinel data in particular is considerable but time, expertise and resources are needed to develop national- or even regional-level data. However, this type of data preparation and collation would have value across research carried out by the EPA and other agencies and is something that should be considered in the future; it could be seen as some sort of “data capital” investment. There are also some interesting examples of crowd-sourced citizen mapping resources in areas such as climate change research that might be interesting to explore.

4.7.1 Final data model: aligned health and GBI data

The final multi- and single-scale sites of interest were identified in section 4.3 and the final stage of the work was to begin to assemble GBI data to match these locations. It was important to keep these two pieces of analysis separate. Although it would have been tempting to follow a GBI-led route – and some preliminary scoping was carried out – the design of the project was for it to be health led and for the matching and association phases to follow this in sequence. There were fewer rural sites than we might have liked, given the overlap with the more urban focus of the detailed available GBI data (UA), although they were identifiable within the national-level coverage provided by the CORINE data set. This is more fully discussed in the following section. In addition, scale issues were a problem in rural area, where an IA, an ED and even a SA in a very remote area might be one and the same. Figure 4.3 provides an example of one of the study areas from Cork City, which shows the underlying IA–ED–SA geography and additionally an extract from UA to show the overlapping GBI data. Visualising both together is difficult to interpret, but it does give a sense of the two strands of data that fed into the modelling. In addition, the use of the background map and the different scales at which layers were digitised will have an effect on the sharpness of the boundaries and explains the slight jittering between the different scales.

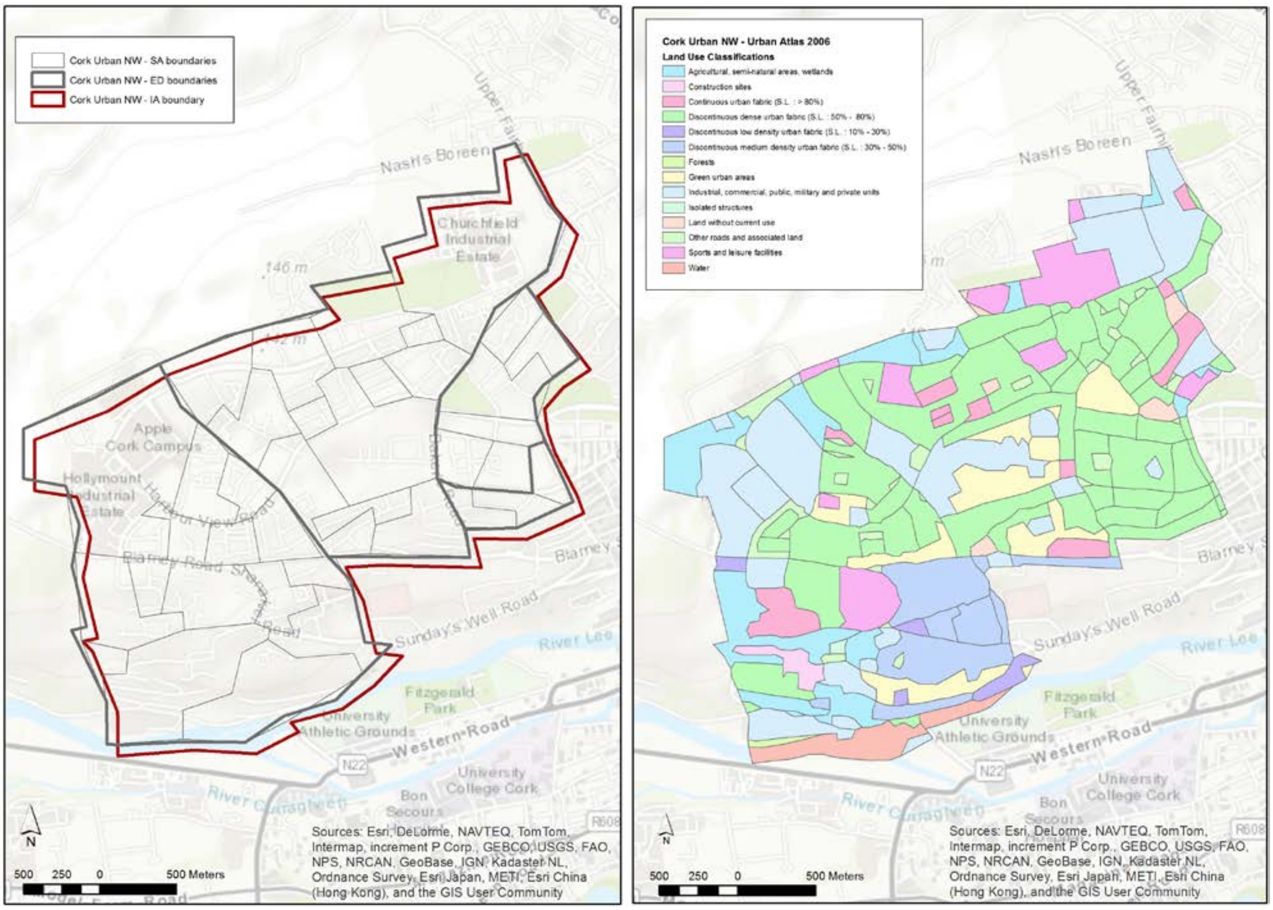

Figure 4.3. Health and GBI data used for the Cork study site modelling. Sources: Ordnance Survey Ireland/CSO, 2018, reproduced under Creative Commons Attribution 4.0 International (CC BY 4.0) licence, and European Environment Agency.

5 Statistical Modelling

5.1 Introduction

A key overall aim of the project was to determine the magnitude of associations of GBI elements with the health indicators for chosen case study areas. This section discusses the results of the statistical modelling WP, which was two-way multi-scale (for identifying the best scale for modelling GBI and human health relationships nationally) and single scale (for more detailed modelling at the identified optimal IA scale)

5.2 Interpretation of the Statistical Results: Sample Sites/Multi-scale

After filtering outliers with good and poor health outcomes from sample sites, relatively good R^2 values were obtained for associations between GBI and health, as well as between socio-economic deprivation/affluence and health. This implied in effect that, irrespective of the cluster samples used in the modelling (either clusters of good health or clusters of poor health), strong associations were observed between the presence and high proportions of GBI and good health and also between socio-economic affluence and good health. In addition, strong associations were also observed between no or low proportions of GBI and bad health and between socio-economic deprivation and bad health, in both good health and bad health clusters (see Appendix 3).

Conversely, some reverse associations, contradicting those expected, were also observed in the sample clusters of good and poor health. We observed strong associations between high socio-economic affluence and long-term disability, as well as between high GPI and BPI and self-reported poor health. These reverse associations are shown in Figure 5.1. Such reverse associations are not impossible in reality because people with high levels of socio-economic affluence and high proportions of green and blue space can have ill health if they do not engage with nature in the green and blue space available. In addition, people with access to a high proportion of GBI may

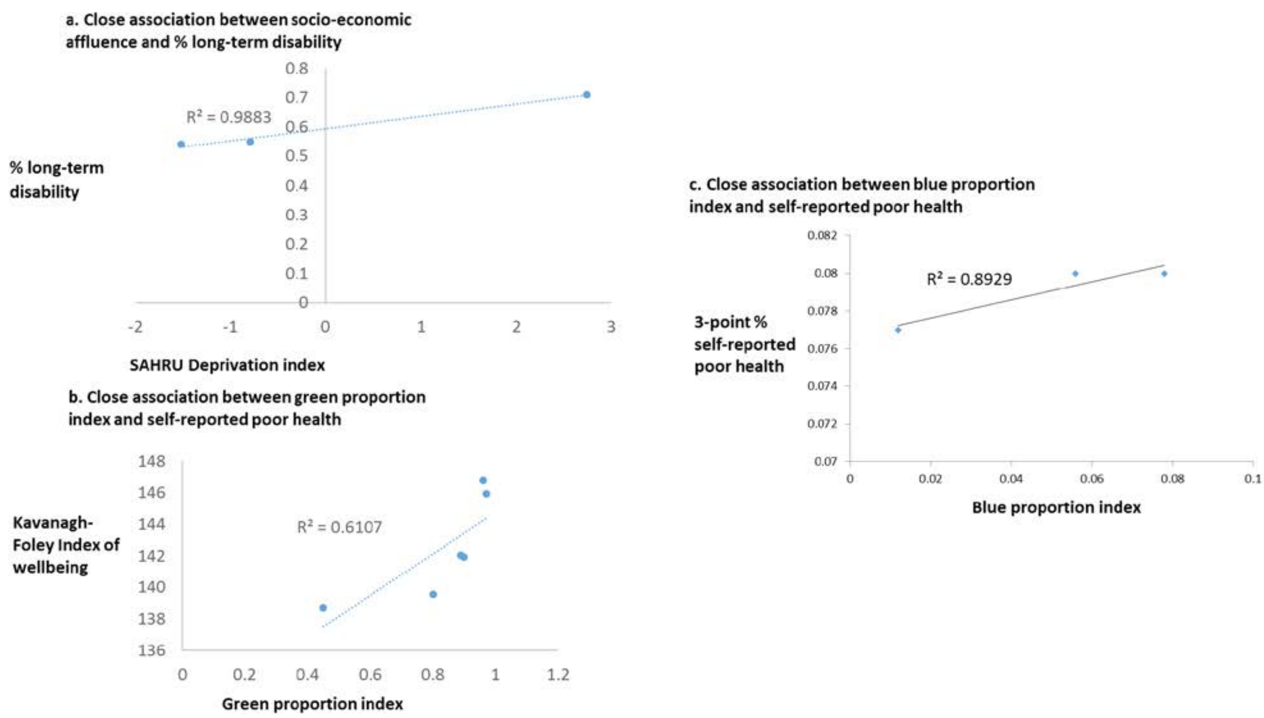

Figure 5.1. Observed reverse associations between GBI and health and between socio-economic deprivation/affluence and health.

be susceptible to poor health despite engaging with nature if they are socio-economically deprived. In the fuller listings in Appendix 3, weak expected associations are designated in yellow, strong expected associations are designated in green, weak reverse associations are designated in red and strong reverse associations are designated in orange.

As observed in Appendix 3, IAs had the highest R^2 in terms of values and frequency. This was followed by the settlement-level geography and then the county-level geography, although we should note the potential impact of small sample sizes across the scales. This implies that associations between GBI and health indicators were stronger at the IA level, followed by settlement level and then county level. Working at settlement scale additionally had the weakness of insufficient representation of blue infrastructure, which was absent in the most frequently appearing clusters of good health obtained from the spatial cluster analysis. This might be an indication that associations between GBI and human health are more sensitive and therefore may be more effectively studied at intermediate geography scale. Numerous zero value data incidences in the mortality data at lower levels were taken care of by aggregating the data up to the IA geography scale. Although IAs are not currently a recognised geography of the CSO, data at smaller scales (ED and SA) can be easily aggregated to IA geography (Rigby *et al*., 2017). Within this study, even though only mortality data were originally produced at IA scale, all other data sets were reproducible and usable at IA scale. Intermediate geography is therefore recommended as a basis for planning GBI interventions, as well as more detailed modelling and finer scale assessments (e.g. at ED and SA scales).

Compared with reduced mortality and disability rates, self-reported good health seemed to have a closer association with the presence of GBI. Reduced mortality rates also seemed to have a closer association with the presence of GBI than decreases in disability rates. However, this might have been because of the incompleteness of the disability data provided and the limited amount of data points for modelling associations between GBI and disability. Easing restrictions and allowing more access to more detailed disability data at all scales may help model the association between GBI and disability more effectively. More detailed data on causes of mortality and classes of disability will also improve understanding of the impact of GBI on disability and mortality.

Associations between GBI and health cannot be said to be markedly different over time. This may be in part because there is no significant difference over time between the GPI and the BPI obtained from the coarse spatial resolution of CORINE land cover information (30 m). Some misclassifications or possible changes in land cover were, however, noticed (mostly from mineral extraction sites to construction sites). Because of the data limitation of the CORINE land cover data sets, modelling at lower scales (ED and SA scales) should be carried out using the UA (with a spatial resolution of 2.5 m) or other finer resolution land cover or satellite imagery. At finer resolution, changes in land cover and corresponding changes in health outcomes, as well as finer associations of GBI with health outcomes, can be expected to be detected. The limitations of UA land cover data, however, lie in the fact that they are available only for big cities across Europe. Modelling at ED and SA scale was not possible within the context of this study because of time constraints. The results of calculating the GPI and the BPI of chosen sample clusters for the multi-scale modelling of the CORINE 2006 and 2012 data are reported partly in Appendix 3. The high degree of sensitivity of the GPI and the BPI to modelling of health outcomes is an indication that they are appropriate for measuring the association between GBI and health.

5.3 Interpretation of the Statistical Results: Case Study Sites/Single-scale

As suggested from the results of the multi-scale modelling, IA geography was adopted for more detailed single-scale modelling using the UA land cover data (spatial resolution of 2.5 m). Although not completed in the timescale of the project, modelling at finer scales (e.g. at ED and SA scales) could extend the modelling into a more multi-scale environment, using the finer detail of UA in the future. However, the difference here was that a different GBI data set was used for the statistical modelling.

Even though the presence of both types of infrastructure, blue and green, would normally be associated with self-reported good health and lower mortality and disability rates, more detailed single-scale modelling from the 10 case study sites revealed that green infrastructure seemed to have better associations with these health indicators than blue infrastructure (Appendix 3). This was reflected by higher R^2 values of associations between green infrastructure indicators (GPI) and health indicators (i.e. indicators of self-reported health, disability and mortality) than between blue infrastructure indicators (BPI) and the same health indicators. It is, however, not certain and, indeed, unlikely that these relationships would hold if the sample sites were larger or if the source data were different, and this can be developed in follow-up work. The perceived weaker associations between blue infrastructure and health indicators were not noticed in the multi-scale modelling using CORINE land cover data. The stronger association of blue infrastructure with health observed in the multi-scale modelling using CORINE data might be because blue infrastructures are better defined in CORINE land cover data. The observed weaker association between blue infrastructure and health indicators in the more detailed single-scale assessment might be because blue infrastructures are not well defined within the UA land cover data, that is, marshes, intertidal flats and wetlands were individual blue infrastructure classes in the CORINE data set but were merged into the mixed class of "agricultural, semi-natural areas and wetlands" in the UA data set.

Reverse associations observed while modelling with the final case study sites indicated that higher socio-economic affluence may be associated with higher mortality and disability rates (Figure 5.2a and b, respectively). This is possible in reality if people of higher socio-economic affluence are predominantly older people (especially close to life expectancy age). This underscores the importance of assessing the impact of age as a confounder variable in subsequent studies. The BPI was also observed to be associated with higher premature mortality rates, that is, mortality under 75 years (Figure 5.2c). This may be possible in reality if there is not enough engagement with surrounding blue infrastructures. Further investigation into this reverse association might be needed to unravel the hidden causes of death in the case study areas and establish their connection or otherwise with surrounding blue infrastructures.

Single-scale modelling revealed conflicting associations between socio-economic affluence and disability rates (Figure 5.3). Weak to strong reverse associations were observed between socio-economic affluence and disability rates (Figure 5.3a–c). Weak associations were also observed between socio-economic deprivation and disability rates (Figure 5.3d).

As was the case with the multi-scale modelling, self-reported good health seemed to have a closer association with the presence of GBI than decreased

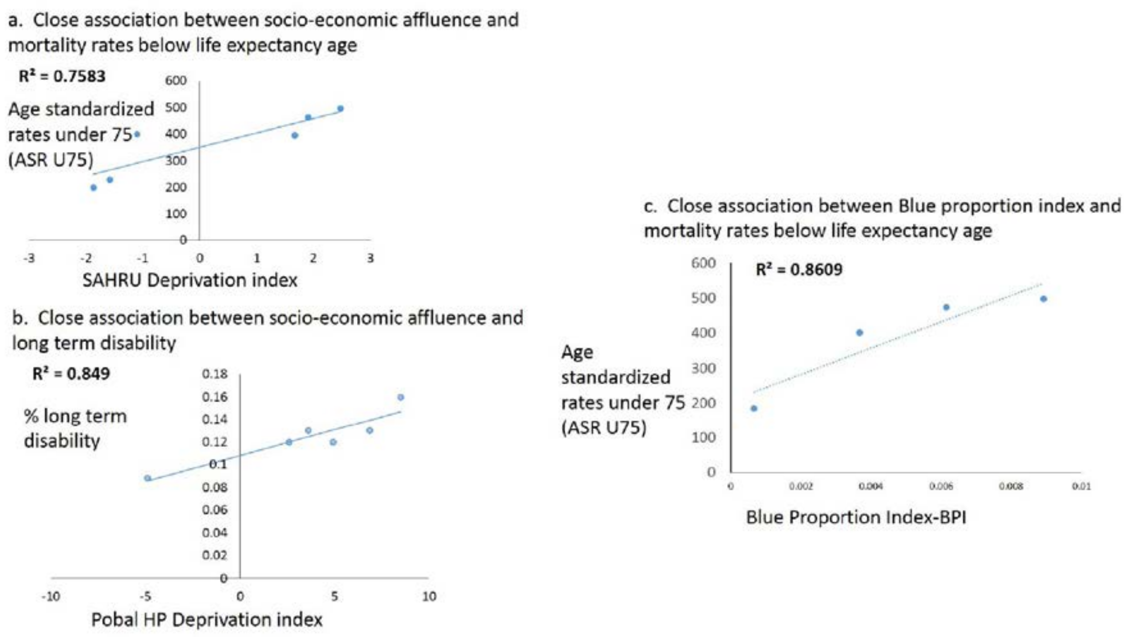

Figure 5.2. Observed reverse associations between blue infrastructure and health and between socio-economic deprivation/affluence and health.

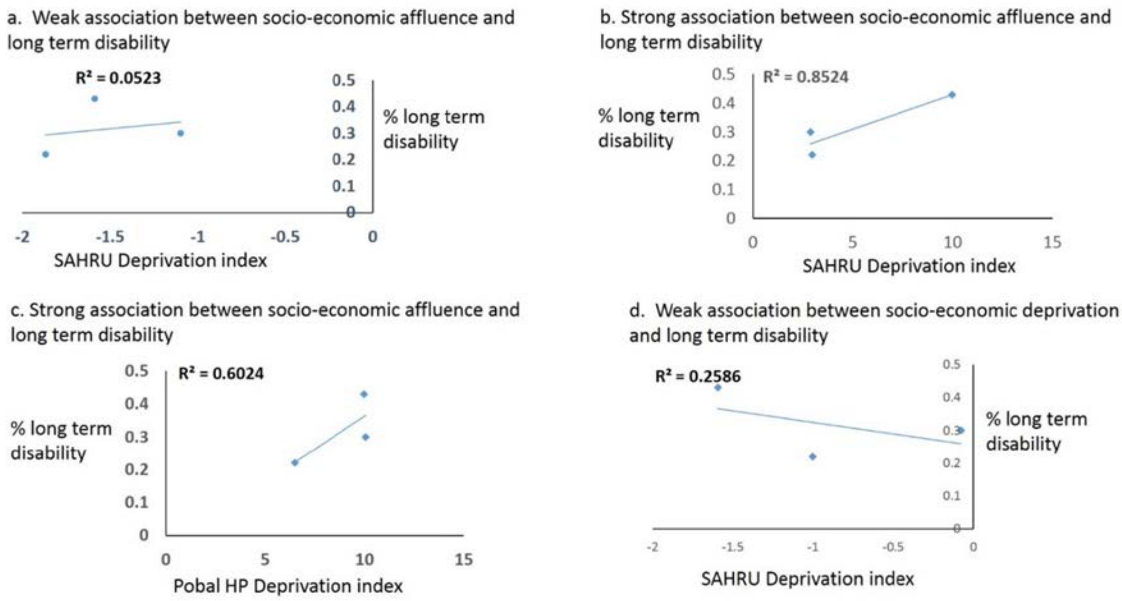

Figure 5.3. Conflicting associations between socio-economic deprivation/affluence and health.

mortality and disability rates. Lower mortality rates also seemed to have a closer association with the presence of GBI than reduced disability rates (i.e. in terms of R^2 values). The conflicting and weak associations between socio-economic affluence/deprivation and disability, as well as the relative weaker associations between reduced disability and the presence of GBI, might be related to the incompleteness of the disability data provided and the insufficiency of data points for the modelling of the different associations. Easing restrictions to access to disability data would help improve future modelling exercises. The conflicting association might, however, have also been a result of the difference in the socio-economic affluence/deprivation index employed by this study. The SAHRU Deprivation Index showed weak associations regardless of the direction of the association. The Pobal HP Deprivation Index on the other hand showed strong associations regardless of the direction of the association. The computation of the Pobal HP Deprivation Index involved replacing initial indicators with newer ones that reflected change in socio-economic paradigms over time (e.g. removal of car ownership as an indicator of socio-economic affluence). The upgraded/newer Pobal HP Deprivation Index might therefore have been more sensitive to health indicators than the SAHRU Deprivation Index. Detailed attention should therefore be given to the composition of deprivation indices (e.g. SAHRU and Pobal HP) within subsequent GBI studies, in order to understand their specific relationships to health outcomes. A useful example of the ways deprivation indices can be focused on specific indicators would be the specific "health domain" sub-score of the UK'S Index of Multiple Deprivation, drawn from 'health-only' variables.

Similar to the multi-scale modelling, associations between GBI and health cannot be said to change over time. Even though finer resolution UA data were used for the calculation of the GPI and BPI, there was no significant difference in the values of GPI and BPI over the two periods over which the UA land cover data were available (2006 and 2012). By extension, there were therefore no marked differences in the association between GBI and human health over the different (and relatively short) time periods examined. This might be the case in reality as health outcomes over time can be greatly influenced by other factors than slight changes in the presence and/or absence of GBIs. As a developed, relatively well-planned country where there are no significant changes in land use over periods of time, the effect on health outcomes of slight changes in the presence and/or absence of GBIs may not be detectable, even though there is evidence pointing to detectable health impacts of GBIs. That said, modelling at finer scales (e.g. at PCN, ED, SA, census tract and land plot scales) still leaves the possibility for the potential detection of changes in health outcomes as a result of slight changes in the presence and/or absence, as well as changes in sizes and structures, of GBIs.

6 Discussion, Conclusion and Recommendations

6.1 Overall Process

This research set out to establish some quantifiable associations between health indicators and outcomes and the extent of and access to GBIs. The project followed the WPs outlined in the initial proposal. WP2 was the literature review and this is described in Chapter 2 of the report. WP3 was the data audit and site selection; the data audit is described in Chapter 3, and Chapter 4 combines a discussion of the choice of sample/case study sites with a discussion of the parallel GBI characterisation (WP4). WP5, the statistical modelling of associations between health and GBI data, is discussed in Chapter 5.

The management of the project was led by the Principal Investigator, Dr Ronan Foley (Maynooth) and Co-principal Investigator, Dr Michael Brennan (EMRA). The bulk of the modelling and drafting work on the empirical parts of the project was carried out by the project's post-doctoral researcher, Dr Oludunsin Arodudu (Maynooth). Expertise around GBI characterisation and statistical modelling was provided by Professor Gerald Mills and Dr Tine Ningal (both University College Dublin [UCD]), whereas an overall policy steer was provided by Malachy Bradley (EMRA). In addition, the project was part of a suite of EPA-funded projects that broadly focused on health and natural environments and joint steering group meetings were held with the NEARHealth project at National University of Ireland (NUI) Galway (http://www.nuigalway.ie/near-health/project/) and the ECOHealth project at UCD (http://www.ecohealth.ie/). In addition, there was a valuable steer from Healthy Ireland, the Department of Health and the HSE, in particular, representatives of the HIU.

6.2 Conclusions and Recommendations

This study presents a substantial GIS-based yet health data-led methodology for the assessment of the effects of GBI on human health. The results of the modelling of the impact of GBI on human health using a health data-led approach (deploying self-reported health, mortality and disability as health indicators) agree with the existing consensus and body of scientific evidence that the presence of GBI contributes to the improvement of health. Irrespective of the approach taken (i.e. GBI led or health led), the argument that the presence or introduction of GBI has potential health benefits is sustained. The specific benefits of a health-led approach, however, lie in the capability to reveal areas of good health and bad health profiles, irrespective of the presence or absence of GBIs, as well as socio-economic deprivation/affluence status. A health data led-approach further stresses the need for adequate consideration of confounder variables when it reveals the characteristics of places of good health and bad health and such characteristics do not conform with conventional (expected) thinking at the GBI and human health research interface. Studies establishing the ranking of the impacts of GBIs on health, compared with the impacts of confounder variables on health, should be prioritised. Although this study revealed that composite socio-economic deprivation/affluence indices (namely the SAHRU Deprivation Index and the Pobal HP Deprivation Index) are sensitive to socio-economic deprivation/affluence and health relationships, other important confounder variables such as environmental factors, climate, age and gender, as well as other health and health-promoting factors, also need to be given adequate consideration within GBI and human health studies. The sensitivity of composite socio-economic deprivation/affluence indices to socio-economic deprivation/affluence and health associations is an indication that they are suitable for use as confounder variables within health-led GBI and human health research. However, as the results from this study suggest that some composite indices might be more sensitive to health outcomes than others, care must be taken in understanding their relationships to health outcomes before they are used within GBI and human health studies. Sample/case study site selection under this study was based on a spatial clustering algorithm (the ALMI statistic), which factored in spatial autocorrelation in the computation of spatial clusters of good and poor health; however, subsequent health-led, GBI and human health studies should test the applicability of other data-clustering algorithms for comparison. Examples of such clustering algorithms include *K*-means clustering, mean shift clustering, density-based clustering, agglomerative hierarchical clustering, expectation minimisation clustering using Gaussian mixture models and two-step clustering. Spatial clustering algorithms might, however, be preferred if the assessment of the spatio-temporal dimensions of health clusters is prioritised in sample/case study site selections. The ALMI algorithm can help reveal change in the status of health clusters (e.g. from HH to LH clusters) over time. The GPI and BPI also proved to be very sensitive as GBI indicators for modelling GBI and human health relationships. Future studies should, however, work on establishing the GPI or BPI needed to maintain healthy environments at different scales as deemed appropriate. This could be done using detailed multiple-level regression modelling or goal-seeking modelling approaches.

Access to and use of more detailed health data, as well as the use of other health indicator data such as prescription rates, frequency of health facility visits and self-reported chronic illness, will help improve the robustness of future studies of this nature. This might be done by widening the scope of determination of clusters of good health and bad health (which was limited to only self-reported health, disability and mortality within this study). IA geography was observed to be very sensitive to the modelling of GBI and human health relationships. It is therefore recommended as a useful scale of geography for future modelling of GBI and human health associations. However, other unexplored geographies that might be sensitive to the modelling of GBI and human health relationships, as well as being good for planning of GBI interventions, include PCNs, EDs, SAs, census tracts and land plots. Finer scale and fuller modelling with larger area counts (at ED and SA scales, etc.) also needs to be carried out to ascertain the sensitivity of the associations of GBI with human health, as well as the feasibility of planning at such scales.

6.3 Potential and Value

We are well aware of some of the gaps and flaws in the modelling and these will be discussed in the next section. However, notwithstanding these issues, the primary aim of the project was to develop what might be characterised as a “proof-of concept” study, to establish and clearly demonstrate the capacity to combine meaningful health and GBI data within a specific area-based context. Gaps could and most likely will be filled in over time or by follow-up studies, but the bones of a method and approach are produced in this report. Another important component of a proof-of-concept study is also to begin to explore gaps and mismatches with existing data as well as approaches and modelling methods that might help close them. In that sense, the joint development of the work with the EPA and HSE, as well as Healthy Ireland, focused attention on issues of geography and data sharing, which considered important aspects of aggregation, scalability, anonymisation and visualisation. We are well aware that these types of discussions are ongoing around health data but we hope that this study will guide and inform these discussions in two key ways: first, by insisting that more comprehensive spatial tagging be an essential component of all future data and metadata development within health, and, second, by specifying the need to pay more attention to the overlaps and co-terminosity of geographical aggregations in the planning and dissemination of health data.

In also drawing attention to ongoing discussions about the sharing of spatial data, we were slightly disappointed in the levels and amounts of health data that met our needs, especially in the sense of these data being easily available and open. We can see some interesting tensions emerging in the face of, on the one hand, a real push for open data and, on the other hand, the introduction of the General Data Protection Regulation (GDPR) from 26 May 2018. In the case of the former, there is a growing demand, both within and outside the health sector, for better and fuller access to meaningful data at usable levels of detail. At a recent discussion within the CSO on planning for the next census in 2021, a representative of the National Disability Authority noted that, for the National Disability Authority, the most meaningful indicator of demand for health-care services is Question 17a on the census form, based on difficulties inside the home. However, these data are not released below settlement level for public use and even then they are released only for the larger settlements.

However, despite the above constraints, it was possible to produce some statistical evidence on the relationships between health indicators and levels of GBI across the sample/case study sites which suggests that a scaled-up version, incorporating fuller data sets on both sides of the equation, would have considerable value.

6.4 Constraints and Issues

Quite apart from the constraints of access and processing, discussed fully above, we also identified a number of other issues with the project's development. Valuable feedback from steering group meetings suggested that it would be good to explore that previously referred to (section 4.6.1) mix of measures that simultaneously models indicators of health gain and health risk. Again, a lack of data and the difficulties of matching point, line and polygon data within the GIS made this difficult. There are some ways to do this and a conversion of the data into raster-based surfaces would be an intriguing development of this work, although this would be highly constrained by the difficulties in matching scales. In addition, the different forms of health data will always be constrained by wider definitional issues, with terms such as health (often used as a proxy for illness), as well as the obvious difficulties associated with self-reported data and a slight over-reliance on the census.

Equally, there is no doubt that our substantially contextual study operated with some very broad assumptions, not least of which were the partial nature of some of the data, including the lack of full sets of data for all scales for suitable comparison across both time and space. In part, the aggregation to the higher-level geography of the IA provided the most robust results, but this was also constrained by the lack of 2016 data. Although settlement-level data are tempting as a focus for policymakers, matching data to that very specific geography outside of the census is very difficult. More importantly, the focus on an area-based associational study meant that the compositional effects (the role played by individual as opposed to place-based factors) were hard to factor in, yet they potentially explain some of the unexpected reverse associations. It is the case that the closer one gets in area-based work to the level of the individual the narrower that gap is between composition and context. In terms of Irish data, the development of estate-level geographies nationally, namely, the SAs, has narrowed that gap considerably, yet access to meaningful health data at this scale remains very hard to operationalise. The development of aggregated administrative data within safe havens based on this scale of data collection would be a valuable way to tackle this gap in the future.

We equally acknowledged that the data sets used on the GBI side, although effective, were not capable of providing some of the nuance required of such modelling. Other longer term studies have been able to develop the use of detailed indicators out of satellite imagery and establish positive and significant associations from such data (Brennan *et al*., 2017). In addition, more nuanced classifications of the type, quality and usability of GBI would need to be factored in (Lachowycz and Jones, 2013). However, the traditional focus on green space has considerable capacity to be given a separate blue tinge, something that this project has partially succeeded in doing.

6.5 Further Work

Despite the limitations of area-based associational work it remains valuable as a screening/scoping stage of work in this area. At the same time, although fuller evidence for individual-level experiences and utilisations of GBI is absent, this would require a very different and much more direct approach, which might in the end be less generalisable. However, the development of work that begins to combine the compositional with the contextual, and the parallel work of Dempsey *et al*. (2017) is a fine example, opens some interesting routes for further research, especially in relation to longitudinal studies that include some behavioural components.

As part of the project we have been fortunate to also attend steering group meetings and other networking events with the parallel NEARHealth and ECOHealth projects. We would identify some synergies between the projects as working towards something that would look like a health impact assessment (HIA). The GBIHealth project provides that initial screening/scoping stage of a HIA, whereas the ECOHealth project at UCD relates to the follow-on planning stage with the general public in exploring how the public understands healthy nature. Finally, the NEARHealth project in NUI Galway provides a stronger steer around public engagement and health promotion initiatives (the final part of a HIA) that have a strong experiential component. What we are really talking about here are different strands of an integrated compositional and contextual approach, which is an explicit aim of the developing EPA-SHEER project [http://sheerwellbeing.insight-centre.org/ (accessed 19 September)]. This research, being developed from the NEARHealth project in NUI Galway and with input from Healthy Ireland and open data partners, will be a more focused place-based multi-methods study that integrates geospatial data sets with a more qualitative and user-led approach, which collectively will identify experiential insights into how people use natural spaces for health gain.

6.6 Additional Recommendations

Although the recommendations above relate to the mixed statistical results of the spatial modelling, it is important to translate these into more applied suggestions for health and environmental agencies for future development. For us, one of the key constraints was issues to do with health data, specifically around availability and effective data matching. In addition, making date more visible spatially, such as through the routine use of a postcode, would also enhance data matching across the services and make future work that combined environmental and health indicators much more effective and robust. In essence, improved inputs linked to the ways that health data are collected, aggregated and disseminated will help researchers produce better-quality reporting that in turn will enhance health service delivery and improve population health for all.

One key suggestion was the *identification of a working intermediate geography (ies)* for health data collection and collation in the future. This may be a combination of service-level units or a new set of boundaries such as the IAs identified in this project. The value of such units/scales would be that they would be built from and be coherent and consistent with CSO data and would also be adaptable to point-based micro-data and other survey data in terms of aggregation. This should form the basis of discussions across many of the policy sectors within which Healthy Ireland operates. This includes regional-level analysis and wider data and evidence on physical activity, some of which can be mapped onto the health data used in this study. The project, through its Principal Investigator, made a formal submission to a May 2018 Department of Health public consultation on the role of geographical boundaries in health-care planning.

Such units might also be linked very specifically to operational geographies across health and social care. A number of existing boundaries and administrative units (not always stable or clear) are used within the HSE and the Department of Health. These include CHOs, LHOs and, especially, the proposed PCNs. Given the suggested mean population of PCNs as being around 50,000, this suggests that the number of such units nationally might be around 95. This would still be a relatively broad reporting geography, but would be much more nuanced than the current LHOs and improve local-level planning. It would also be a service-derived scale to which individual-level data could be safely aggregated to.

A further suggestion is greater consideration of the *routine (or retrospective) use of spatial tags* such as Eircode in data recording. This would simplify and speed up the aggregation of health data into larger reporting areas, and provide a much more robust evidence base for any subsequent data analysis, while at the same time safeguarding the data from disclosure. A recent study presented as a poster at UCD in April 2018 showed the potential of mapping geo-located individual-level HIPE data at ED level to identify direct hospital catchments for the first time (O'Mahony *et al*., 2018).

A final suggestion, especially relevant to improved combinations of environment and health data, would be the *development of shared and agreed GBI data sets*, derived from recent satellite data and gathered and standardised across regular time periods that align with other periods of data collection. Although CORINE and UA do this to an extent, there are many more regularly collected data coming on stream, albeit requiring some expert preparation. These should incorporate some additional metrics on area type, shape and complexity, as well as, when possible, more nuanced classifications of GBIs that, in turn, provide better information on how they can enhance and promote health and well-being.

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Abbreviations

AIRO	All-Ireland Research Observatory
ALMI	Anselin Local Moran's I
ANOVA	Analysis of variance
BPI	Blue (infrastructure) proportion index
CHG	Centre for Health Geoinformatics
CHO	Community health-care organisation
CORINE	Coordination of Information on the Environment
CSO	Central Statistics Office
ED	Electoral division
EMRA	Eastern and Midlands Regional Assembly
EPA	Environmental Protection Agency
EU	European Union
GBI	Green and blue infrastructure
GIS	Geographic information system
GMS	General Medical Services
GPI	Green (infrastructure) proportion index
GUI	Growing Up in Ireland
HH	High–high
HIA	Health impact assessment
HIPE	Hospital In-Patient Enquiry
HIQA	Health Information and Quality Authority
HIU	Health Intelligence Unit
HL	High–low
HRB	Health Research Board
HSE	Health Service Executive
IA	Intermediate area
KFIW	Kavanagh–Foley Index of Wellbeing
LA	Local authority
LH	Low–high
LHO	Local health office
LL	Low–low
MAUP	Modifiable areal unit problem
NDVI	Normalised Difference Vegetation Index
NUI	National University of Ireland
OECD	Organisation for Economic Co-operation and Development
PCN	Primary care network
SA	Small area
SAHRU	Small Area Health Research Unit
SAPS	Small Area Population Statistics
TILDA	The Irish Longitudinal Study on Ageing
UA	Urban Atlas
UCD	University College Dublin
WP	Work package

Appendix 1 Core Metadata for Representative Data Sets Chosen for Detailed Use

Table A1.1. Mortality

Field	Description
Name	Mortality
Type	Measured
Code	M1
Method	Formal record
Question	Completed official returns of coroners
Data holder	Centre for Health Geoinformatics, Maynooth University
Access status	Publicly available
Source	www.chg.ie
Form(s)	xls table, shapefile
Years	2006–2011 inclusive (2012–2014 also completed)
National	Not Available
Settlement	Not Available
IA	Y
ED	N
SA	N
Notes	Data collected from annual death record returns (manual). Data published with 2-year lag
Status	3

Table A1.2. Census health status

Field	Description
Name	Census health status
Type	Self-reported
Code	SR1
Method	Collected via national census
Question	Five-part census health question (very good, good, fair, bad, very bad)
Data holder	CSO
Access status	Publicly available
Source	www.cso.ie
Form(s)	xls table, shapefile
Years	2011, 2016
National	Y
Settlement	Y
IA	Y
ED	Y
SA	Y
Notes	Data taken from Q18 on 2016 census form
Status	1

Table A1.3. Census disability status

Field	Description
Name	Census disability status
Type	Self-reported
Code	SR2
Method	Collected via national census
Question	Seven-part census question on long-lasting illness/impairments (vision, hearing, physical, Intellectual Disability, memory, emotional, chronic)
Data holder	CSO
Access status	Publicly available
Source	www.cso.ie
Form(s)	xls table, shapefile
Years	2011, 2016
National	Y
Settlement	Y
IA	N
ED	Y (as total recording of disability only)
SA	Y (as total recording of disability only)
Notes	Data taken from Q16 on 2016 census form
Status	2

Table A1.4. Pobal HP Index of Deprivation

Field	Description
Name	Pobal HP Index of Deprivation
Type	Derived
Code	D1
Method	Modelled via national census data
Question	Based on a large number of census questions across different domains
Data holder	CSO, Pobal, Trutz Haase Consultants
Access status	Publicly available
Source	https://maps.pobal.ie/
Form(s)	xls table, shapefile
Years	1996, 2002, 2006, 2011, 2016
National	Not Relevant
Settlement	Currently Not Available
IA	Currently Not Available
ED	Y
SA	Y
Notes	Data derived from multiple variables from the census, categorised into broad demographic, social class and labour market dimensions
Status	2

Table A1.5. SAHRU Deprivation Index

Field	Description
Name	SAHRU Deprivation Index
Type	Derived
Code	D2
Method	Modelled via national census data
Question	Based on four census questions
Data holder	CSO, Trinity College Dublin
Access status	Publicly available
Source	www.tcd.ie/medicine/public_health_primary_care/research/
Form(s)	xls table, shapefile
Years	1996, 2002, 2006, 2011, 2016
National	NR
Settlement	Currently NA
IA	Currently NA
ED	Y
SA	Y
Notes	Initially created via the SAHRU at Trinity College Dublin and still updated by Trinity College Dublin after the closure of SAHRU
Status	2

Table A1.6. Kavanagh–Foley Index of Wellbeing

Field	Description
Name	KFIW
Type	Derived
Code	D3
Method	Modelled via national census data
Question	Based on five-part census health question (very good, good, fair, bad, very bad)
Data holder	Department of Geography, Maynooth University
Access status	Publicly available
Source	Contact ronan.foley@mu.ie
Form(s)	xls table, shapefile
Years	2011, 2016
National	Y
Settlement	Y
IA	Y
ED	Y
SA	Y
Notes	Created by staff in the Department of Geography, Maynooth University, based on a scoring system that weights the different normalised data on self-reported health from the census as follows: very good (1), good (2), fair (3), bad (4), very bad (5). The mean score across all scales is between 147 and 150
Status	2

Appendix 2 Land Use Classification Schemes

Table A2.1. CORINE

Level 1 code	Level 1 description	Level 2 code	Level 2 description	Level 3 code	Level 3 description
1	Artificial surfaces	11	Urban fabric	111	Continuous urban fabric
1	Artificial surfaces	11	Urban fabric	112	Discontinuous urban fabric
1	Artificial surfaces	12	Industrial, commercial and transport units	121	Industrial and commercial units
1	Artificial surfaces	12	Industrial, commercial and transport units	122	Road and rail network
1	Artificial surfaces	12	Industrial, commercial and transport units	123	Sea ports
1	Artificial surfaces	12	Industrial, commercial and transport units	124	Airports
1	Artificial surfaces	13	Mines, dumps and construction sites	131	Mineral extraction sites
1	Artificial surfaces	13	Mines, dumps and construction sites	132	Dump
1	Artificial surfaces	13	Mines, dumps and construction sites	133	Construction sites
1	Artificial surfaces	14	Artificial non-agricultural vegetated areas	141	Green urban areas
1	Artificial surfaces	14	Artificial non-agricultural vegetated areas	142	Sport and leisure facilities
2	Agricultural areas	21	Arable land	211	Non-irrigated arable land
2	Agricultural areas	21	Arable land	212	Permanently irrigated land
2	Agricultural areas	21	Arable land	213	Rice fields
2	Agricultural areas	22	Permanent crops	221	Vineyards
2	Agricultural areas	22	Permanent crops	222	Fruit tree and berry plantations
2	Agricultural areas	22	Permanent crops	223	Olive groves
2	Agricultural areas	23	Pastures	231	Pastures
2	Agricultural areas	24	Heterogeneous agricultural areas	241	Annual crops associated with permanent crops
2	Agricultural areas	24	Heterogeneous agricultural areas	242	Complex cultivation patterns
2	Agricultural areas	24	Heterogeneous agricultural areas	243	Agricultural land with significant areas of natural vegetation
2	Agricultural areas	24	Heterogeneous agricultural areas	244	Agro-forestries
3	Forest and semi-natural areas	31	Forest	311	Broad-leaved forests
3	Forest and semi-natural areas	31	Forest	312	Coniferous forests
3	Forest and semi-natural areas	31	Forest	313	Mixed forests
3	Forest and semi-natural areas	32	Scrub and/or herbaceous vegetation associations	321	Natural grassland
3	Forest and semi-natural areas	32	Scrub and/or herbaceous vegetation associations	322	Moors and heathlands
3	Forest and semi-natural areas	32	Scrub and/or herbaceous vegetation associations	323	Sclerophyllous vegetation
3	Forest and semi-natural areas	32	Scrub and/or herbaceous vegetation associations	324	Transitional woodland scrub

Table A2.1. Continued

Level 1 code	Level 1 description	Level 2 code	Level 2 description	Level 3 code	Level 3 description
3	Forest and semi-natural areas	33	Open spaces with little or no vegetation	331	Beaches, dunes, sand
3	Forest and semi-natural areas	33	Open spaces with little or no vegetation	332	Bare rocks
3	Forest and semi-natural areas	33	Open spaces with little or no vegetation	333	Sparsely vegetated areas
3	Forest and semi-natural areas	33	Open spaces with little or no vegetation	334	Burnt areas
3	Forest and semi-natural areas	33	Open spaces with little or no vegetation	335	Glaciers and permanent snowfields
4	Wetlands	41	Inland wetlands	411	Inland marshes
4	Wetlands	41	Inland wetlands	412	Peat bogs
4	Wetlands	42	Coastal wetlands	421	Salt marshes
4	Wetlands	42	Coastal wetlands	422	Salines
4	Wetlands	42	Coastal wetlands	423	Intertidal flats
5	Water bodies	51	Continental waters	511	Stream courses
5	Water bodies	51	Continental waters	512	Water bodies
5	Water bodies	52	Marine waters	521	Coastal lagoons
5	Water bodies	52	Marine waters	522	Estuaries
5	Water bodies	52	Marine waters	523	Sea and ocean

Table A2.2. Urban Atlas classification scheme

Code	Land use (UA)
11100	Continuous urban fabric (Sealing Layer > 80%)
11210	Discontinuous dense urban fabric (Sealing Layer: 50–80%)
11220	Discontinuous medium density urban fabric (Sealing Layer: 30–50%)
12100	Industrial, commercial, public, military and private units
11300	Isolated structures
12100	Industrial, commercial, public, military and private units
13100	Mineral extraction and dump sites
13300	Construction sites
13400	Land without current use
14100	Green urban areas
14200	Sports and leisure facilities
20000	Agricultural + semi-natural areas + wetlands
30000	Forests
50000	Water bodies

Appendix 3 Summary Statistical Results for Multi- and Single-scale Modelling

A3.1 Sample areas

A3.1.1 Health clusters 1 high–high

Scale (count)	Mortality < 75 years			2-point good health			2-point bad health			3-point bad health			KFIW score			% Disability		
	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016
Green index																		
LA ($n=6$)	0.81	0.73	N/A	N/A	0.99	0.29	N/A	0.99	0.18	N/A	≈1	0.99	N/A	≈1	0.61	N/A	0.43	0.033
IA ($n=8$)	0.89	N/A	N/A	N/A	≈1	0.87	N/A	0.93	0.99	N/A	1	0.85	N/A	N/R	0.8	N/A	0.84	0.4
Settlement ($n=17$)	0.8	0.6	N/A	N/A	0.93	0.99	N/A	N/R	N/R	N/A	0.93	0.93	N/A	0.91	0.85	N/A	N/A	0.92
Blue index																		
LA ($n=6$)	0.84	0.98	N/A	N/A	0.9	0.99	N/A	0.036	0.85	N/A	0.89	0.98	N/A	0.54	0.88	N/A	0.65	0.99
IA ($n=8$)	0.86	N/A	N/A	N/A	0.75	0.98	N/A	0.94	N/R	N/A	0.73	N/R	N/A	0.85	0.79	N/A	0.3	0.57
Settlement ($n=17$)	0.94	0.96	N/A	N/A	1	0.89	N/A	0.89	0.94	N/A	1	0.94	N/A	0.96	0.99	N/A	N/A	0

***R*-squared values: GBI/health indicator.**

Yellow, weak expected associations; green, strong expected associations; red, weak reverse associations; orange, strong reverse associations.

N/A, not available; N/R, not relevant.

A3.1.2 Health clusters 2 low–low

Scale (count)	Mortality < 75 years			2-point good health			2-point bad health			3-point bad health			KFIW score			% Disability		
	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016
Green index																		
LA ($n=6$)	0.76	N/A	N/A	N/A	≈1	0.87	N/A	0.93	0.99	N/A	1	0.85	N/A	≈1	0.8	N/A	0.84	0.4
IA ($n=11$)	0.89	0.96	N/A	N/A	0.86	0.75	N/A	0.83	N/R	N/A	N/R	N/R	N/A	0.58	0.52	N/A	0.93	N/R
Settlement ($n=12$)	N/A	N/A	N/A	N/A	0.75	0.8	N/A	0.54	0.78	N/A	0.59	0.51	N/A	0.64	0.82	N/A	0.052	0.1
Blue index																		
LA ($n=9$)	0.78	N/A	N/A	N/A	0.75	0.98	N/A	0.94	N/R	N/A	0.73	N/R	N/A	0.85	0.79	N/A	0.3	0.57
IA ($n=11$)	0.86	0.32	N/A	N/A	0.34	0.89	N/A	0.26	0.26	N/A	0.99	0.99	N/A	0.9	0.91	N/A	0.17	0.64
Settlement ($n=12$)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

***R*-squared values: GBI/health indicator.**

Yellow, weak expected associations; green, strong expected associations; red, weak reverse associations; orange, strong reverse associations.

N/A, not available; N/R, not relevant.

A3.2 Study sites ($n = 10$)

Scale (count)	Mortality <75 years			2-point good health			2-point bad health			3-point bad health			KFIW score			% Disability		
	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016	2006	2011	2016
Green index																		
GBI 1 IA ($n = 10$)	0.99	N/A	N/A	N/A	N/R	0.99	N/A	0.98	N/R	N/A	N/R	N/R	N/A	0.97	N/R	N/A	0.99	0.99
GBI 2 IA ($n = 10$)	0.73	N/A	N/A	N/A	0.98	0.99	N/A	0.98	N/R	N/A	N/R	0.86	N/A	0.97	0.8	N/A	0.99	0.94
GBI 3 IA ($n = 10$)	0.86	N/A	N/A	N/A	N/R	N/R	N/A	0.99	N/R	N/A	0.97	N/R	N/A	N/R	0.92	N/A	N/R	0.76
Blue index																		
IA ($n = 10$)	0.73	N/A	N/A	N/A	0.9	0.72	N/A	0.84	0.85	N/A	N/R	0.75	N/A	N/R	0.84	N/A	0.84	0.19

***R*-squared values: GBI/health indicator.**

Yellow, weak expected associations; green, strong expected associations; red, weak reverse associations; orange, strong reverse associations.

N/A, not available; N/R, not relevant.

AN GHNÍOMHAIREACHT UM CHAOMHNÚ COMHSHAOIL
Tá an Ghníomhaireacht um Chaomhnú Comhshaoil (GCC) freagrach as an gcomhshaol a chaomhnú agus a fheabhsú mar shócmhainn luachmhar do mhuintir na hÉireann. Táimid tiomanta do dhaoine agus don chomhshaol a chosaint ó éifeachtaí díobhálacha na radaíochta agus an truaillithe.

Is féidir obair na Gníomhaireachta a roinnt ina trí phríomhréimse:

Rialú: *Déanaimid córais éifeachtacha rialaithe agus comhlíonta comhshaoil a chur i bhfeidhm chun torthaí maithe comhshaoil a sholáthar agus chun díriú orthu siúd nach gcloíonn leis na córais sin.*

Eolas: *Soláthraímid sonraí, faisnéis agus measúnú comhshaoil atá ar ardchaighdeán, spriocdhírithe agus tráthúil chun bonn eolais a chur faoin gcinnteoireacht ar gach leibhéal.*

Tacaíocht: *Bímid ag saothrú i gcomhar le grúpaí eile chun tacú le comhshaol atá glan, táirgiúil agus cosanta go maith, agus le hiompar a chuirfidh le comhshaol inbhuanaithe.*

Ár bhFreagrachtaí

Ceadúnú
Déanaimid na gníomhaíochtaí seo a leanas a rialú ionas nach ndéanann siad dochar do shláinte an phobail ná don chomhshaol:
- saoráidí dramhaíola *(m.sh. láithreáin líonta talún, loisceoirí, stáisiúin aistrithe dramhaíola)*;
- gníomhaíochtaí tionsclaíocha ar scála mór *(m.sh. déantúsaíocht cógaisíochta, déantúsaíocht stroighne, stáisiúin chumhachta)*;
- an diantalmhaíocht *(m.sh. muca, éanlaith)*;
- úsáid shrianta agus scaoileadh rialaithe Orgánach Géinmhodhnaithe *(OGM)*;
- foinsí radaíochta ianúcháin *(m.sh. trealamh x-gha agus radaiteiripe, foinsí tionsclaíocha)*;
- áiseanna móra stórála peitril;
- scardadh dramhuisce;
- gníomhaíochtaí dumpála ar farraige.

Forfheidhmiú Náisiúnta i leith Cúrsaí Comhshaoil
- Clár náisiúnta iniúchtaí agus cigireachtaí a dhéanamh gach bliain ar shaoráidí a bhfuil ceadúnas ón nGníomhaireacht acu.
- Maoirseacht a dhéanamh ar fhreagrachtaí cosanta comhshaoil na n-údarás áitiúil.
- Caighdeán an uisce óil, arna sholáthar ag soláthraithe uisce phoiblí, a mhaoirsiú.
- Obair le húdaráis áitiúla agus le gníomhaireachtaí eile chun dul i ngleic le coireanna comhshaoil trí chomhordú a dhéanamh ar líonra forfheidhmiúcháin náisiúnta, trí dhíriú ar chiontóirí, agus trí mhaoirsiú a dhéanamh ar leasúchán.
- Cur i bhfeidhm rialachán ar nós na Rialachán um Dhramhthrealamh Leictreach agus Leictreonach (DTLL), um Shrian ar Shubstaintí Guaiseacha agus na Rialachán um rialú ar shubstaintí a ídíonn an ciseal ózóin.
- An dlí a chur orthu siúd a bhriseann dlí an chomhshaoil agus a dhéanann dochar don chomhshaol.

Bainistíocht Uisce
- Monatóireacht agus tuairisciú a dhéanamh ar cháilíocht aibhneacha, lochanna, uiscí idirchriosacha agus cósta na hÉireann, agus screamhuiscí; leibhéil uisce agus sruthanna aibhneacha a thomhas.
- Comhordú náisiúnta agus maoirsiú a dhéanamh ar an gCreat-Treoir Uisce.
- Monatóireacht agus tuairisciú a dhéanamh ar Cháilíocht an Uisce Snámha.

Monatóireacht, Anailís agus Tuairisciú ar an gComhshaol
- Monatóireacht a dhéanamh ar cháilíocht an aeir agus Treoir an AE maidir le hAer Glan don Eoraip (CAFÉ) a chur chun feidhme.
- Tuairisciú neamhspleách le cabhrú le cinnteoireacht an rialtais náisiúnta agus na n-údarás áitiúil *(m.sh. tuairisciú tréimhsiúil ar staid Chomhshaol na hÉireann agus Tuarascálacha ar Tháscairí)*.

Rialú Astaíochtaí na nGás Ceaptha Teasa in Éirinn
- Fardail agus réamh-mheastacháin na hÉireann maidir le gáis cheaptha teasa a ullmhú.
- An Treoir maidir le Trádáil Astaíochtaí a chur chun feidhme i gcomhair breis agus 100 de na táirgeoirí dé-ocsaíde carbóin is mó in Éirinn.

Taighde agus Forbairt Comhshaoil
- Taighde comhshaoil a chistiú chun brúnna a shainaithint, bonn eolais a chur faoi bheartais, agus réitigh a sholáthar i réimsí na haeráide, an uisce agus na hinbhuanaitheachta.

Measúnacht Straitéiseach Timpeallachta
- Measúnacht a dhéanamh ar thionchar pleananna agus clár beartaithe ar an gcomhshaol in Éirinn *(m.sh. mórphleananna forbartha)*.

Cosaint Raideolaíoch
- Monatóireacht a dhéanamh ar leibhéil radaíochta, measúnacht a dhéanamh ar nochtadh mhuintir na hÉireann don radaíocht ianúcháin.
- Cabhrú le pleananna náisiúnta a fhorbairt le haghaidh éigeandálaí ag eascairt as taismí núicléacha.
- Monatóireacht a dhéanamh ar fhorbairtí thar lear a bhaineann le saoráidí núicléacha agus leis an tsábháilteacht raideolaíochta.
- Sainseirbhísí cosanta ar an radaíocht a sholáthar, nó maoirsiú a dhéanamh ar sholáthar na seirbhísí sin.

Treoir, Faisnéis Inrochtana agus Oideachas
- Comhairle agus treoir a chur ar fáil d'earnáil na tionsclaíochta agus don phobal maidir le hábhair a bhaineann le caomhnú an chomhshaoil agus leis an gcosaint raideolaíoch.
- Faisnéis thráthúil ar an gcomhshaol ar a bhfuil fáil éasca a chur ar fáil chun rannpháirtíocht an phobail a spreagadh sa chinnteoireacht i ndáil leis an gcomhshaol *(m.sh. Timpeall an Tí, léarscáileanna radóin)*.
- Comhairle a chur ar fáil don Rialtas maidir le hábhair a bhaineann leis an tsábháilteacht raideolaíoch agus le cúrsaí práinnfhreagartha.
- Plean Náisiúnta Bainistíochta Dramhaíola Guaisí a fhorbairt chun dramhaíl ghuaiseach a chosc agus a bhainistiú.

Múscailt Feasachta agus Athrú Iompraíochta
- Feasacht chomhshaoil níos fearr a ghiniúint agus dul i bhfeidhm ar athrú iompraíochta dearfach trí thacú le gnóthais, le pobail agus le teaghlaigh a bheith níos éifeachtúla ar acmhainní.
- Tástáil le haghaidh radóin a chur chun cinn i dtithe agus in ionaid oibre, agus gníomhartha leasúcháin a spreagadh nuair is gá.

Bainistíocht agus struchtúr na Gníomhaireachta um Chaomhnú Comhshaoil
Tá an ghníomhaíocht á bainistiú ag Bord lánaimseartha, ar a bhfuil Ard-Stiúrthóir agus cúigear Stiúrthóirí. Déantar an obair ar fud cúig cinn d'Oifigí:
- An Oifig um Inmharthanacht Comhshaoil
- An Oifig Forfheidhmithe i leith cúrsaí Comhshaoil
- An Oifig um Fianaise is Measúnú
- Oifig um Chosaint Radaíochta agus Monatóireachta Comhshaoil
- An Oifig Cumarsáide agus Seirbhísí Corparáideacha

Tá Coiste Comhairleach ag an nGníomhaireacht le cabhrú léi. Tá dáréag comhaltaí air agus tagann siad le chéile go rialta le plé a dhéanamh ar ábhair imní agus le comhairle a chur ar an mBord.

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Green and Blue Spaces and Health: A Health-led Approach

Authors: Ronan Foley, Michael Brennan, Oludunsin Arodudu, Gerald Mills, Tine Ningal and Malachy Bradley

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Climate - Water - Sustainability
Identifying pressures • Informing policy • Developing solutions

Identifying Pressures

Ireland is faced with a generally healthy although ageing population. However, public health concerns have been expressed about high levels of obesity and increasingly sedentary lifestyles as being contributors to potentially declining future public health outcomes. One research area identified as having the potential to combat such pressures has been the health potential of natural environments, expressed here as green and blue infrastructure (GBI). The literature identifies generally strong positive relationships between access to and the availability of GBI with better health and well-being indicators. This study addresses these pressures through spatial (geographical) modelling in Ireland, looking at identifying a measureable effect from the relationships between different indicators of health and levels of GBI. Unlike other studies, we consider this pressure from a "health-led" position, with a core focus on the health end of that health/environment equation.

Informing Policy

Using innovative Geographic Information Systems (GIS), spatial modelling and statistical analysis, this study identifies evidence for the direct relationships between the presence of GBI and a number of health indicators, including self-reported health, mortality and disability, with additional mediation from deprivation. The health indicators used in the study were focused on publicly available data at a range of aggregated spatial scales, from small area up to county level. In addition, the report provides a critical data audit on both barriers to and positive suggestions on ways to develop a fuller public evidence base for area-based health research. The findings will inform a number of national agencies and service providers, including the Health Service Executive, the Department of Health and the cross-departmental Healthy Ireland initiative.

Developing Solutions

Using statistical modelling for a small number of sample areas against two different GBI datasets, this report documents magnitudes of associations of GBI elements with health status. It also identifies a pathway for further work in two ways: first, by demonstrating techniques to collate, overlay and aggregate health data across different scales of analysis, and, second, by providing a critical analysis on the availability of health data, with an emphasis on gaps and access issues, but also opportunities associated with the rapidly developing availability of health data. The report directly suggests the need for a new intermediate area geography for the reporting of health data in Ireland that would be mutually acceptable to data holders and data users.

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