Implementing the Decent Homes Standard in the Private Rented Sector: Introducing the Non-Decent Index

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Declaration

A draft version of this report and the Non-Decent Index was submitted to the 2024 Thinkhouse Early Career Researcher's Prize – see Marshall, M. (2024). *The spatial distribution of non-decent homes: Introducing the Non-Decent Index*. This report, and the work contained within, supersedes the analysis presented in the draft report.

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Executive Summary

The English housing stock is among the oldest in Europe and enduring issues of condition and quality contribute to further inequalities in health and wellbeing (Clair and Baker, 2019; Clair and Hughes, 2019). Bringing the nation's housing up to minimum standards of decency represents an important objective for research, policy and practice. The Decent Homes Standard (DHS) provides a statutory minimum standard of provision for social housing and a recognised benchmark for housing condition and quality. The UK Government has announced plans to enforce an updated Decent Homes Standard (DHS) from 2035 and to extend the Standard to the private rented sector (PRS), where standards have historically lagged.

DHS reform represents a generational opportunity to improve the quality of the PRS. Yet a lack of freely accessible and granular data on the location of non-decent PRS homes is an ongoing challenge that hinders efforts to improve standards. This challenge is most relevant to local authorities who will be responsible for enforcing the DHS in private rented homes. This report aims to address this gap by introducing the Non-Decent Index (NDI), a publicly available index that can be used to identify Lower Super Output Areas (LSOAs) with a high expected number of non-decent PRS homes, and consequently where greatest attention is required to improve conditions.

The NDI is constructed using a population disaggregation technique that produces small area estimates of DHS compliance within the PRS, which are subsequently weighted by the size of the PRS relative to all other LSOAs. Therefore, the NDI strikes a balance between two indicators – areas with a high proportion of PRS homes failing the DHS, and areas with a large PRS overall. Both indicators will be relevant to resourcing and communicating the rollout of the DHS.

The NDI is validated using national measures of housing deprivation and local authority inspection data from Leeds City Council (LCC). The LCC data demonstrates that areas with a high density of health and safety hazards tend to have a higher NDI, giving confidence as to the index's accuracy.

The NDI can be used as an analytical tool to identify hotspots of DHS failure. This report illustrates using archetypal areas and identifies several risk factors associated with a high NDI, including property age, type, heating source, and energy efficiency rating. The analysis shows that in many English urban areas, the PRS has become spatially concentrated around neighbourhoods of older, terraced housing with poor thermal efficiency. However, high NDI LSOAs also exist in rural areas, especially those off the gas-grid.

The report considers the potential applications of the NDI among researchers and practitioners, including to:

- Target communications with landlords and tenants ahead of the implementation of the DHS in the PRS
- Target local authority inspections in the PRS

- Evidence the need for place-based interventions e.g. selective licensing
- Understand and analyse rental submarkets

Nonetheless, the NDI has some limitations. The NDI provides a snapshot in time and is most appropriately used as a strategic tool to direct attention and resources, rather than as a tool to measure change over time. It is also based upon the current DHS rather than the forthcoming updated Standard. Further work could be undertaken to improve the NDI and further validate the accuracy of its predictions, but this would likely require a substantial data collection exercise involving property inspections.

Access to the NDI can be found through the following links:

- A repository containing the NDI dataset
- An application allowing users to visualise the NDI within individual local authorities

Introduction

The English housing stock is among the oldest in Europe and enduring issues of condition and quality contribute to further inequalities in health and wellbeing (Clair and Baker, 2019; Clair and Hughes, 2019). Bringing the nation's housing up to minimum standards of decency and minimising the prevalence of health and safety hazards in the home, represents an important objective for research, policy and practice. The Decent Homes Standard (DHS) provides a statutory minimum standard of condition for social housing and has become a recognised benchmark of housing condition and quality. The current UK government is implementing landmark legislative changes to the DHS, including updating the DHS for the first time since 2006 (see Box 1), and extending the Standard to the private rented sector (PRS) through the Renters' Rights Act.

The updated DHS will apply to both rented sectors from 2035, although standards regarding thermal comfort are to be in effect from 2030. The new DHS is intended to align standards of thermal efficiency with overarching net zero objectives, ensure homes provide adequate facilities for modern lifestyles, shift landlord practice towards a more preventative maintenance approach, and remove acute health and safety harms from rental housing such as damp and mould (MHCLG, 2026a). Furthermore, the extension of the DHS to the PRS is intended to address systemic inequalities between tenures in housing conditions. In 2024, 22% of PRS properties were non-decent, compared to 15% among owner-occupiers and 10% in social housing (MHCLG, 2026b). Previous research has demonstrated that variation between tenures in DHS compliance cannot be explained simply by differences between tenures in the age or structure of their dwellings (Marshall, 2024).

DHS reform represents a generational opportunity to improve the quality of English housing. Yet a lack of open and granular data on the location of non-decent homes is an ongoing challenge that inhibits the improvement of PRS standards. This challenge is most relevant to local authorities who will be responsible for enforcing the DHS in private rented homes. Official statistics on DHS compliance are provided by the annual English Housing Survey (EHS), but sample sizes are only sufficient for reporting at the regional level. The Ministry of Housing, Communities & Local Government (MHCLG) provides estimates of PRS DHS compliance at the local authority district level (see below), but not the neighbourhood level. A neighbourhood level indicator of housing quality is available through the Indices of Multiple Deprivation (IMD), which includes an estimate of the proportion of homes failing the DHS at the Lower Super Output Area (LSOA) level, known as the 'housing in poor condition' indicator. But this is across all tenures and therefore cannot be disaggregated to the PRS, where targeted action is most needed. Commercial data on health and safety hazards in the PRS is available, but the scale of the challenge in improving PRS standards demands open data in the public domain, focused on DHS compliance specifically. Therefore, there remains a gap in terms of freely available data on

PRS DHS compliance that is transparent in terms of its methodology, validation and limitations.

Box 1: Summary of the 2006 and new Decent Homes Standards

The following comparison outlines the core DHS criteria and the key changes between the 2006 iteration and the new reformed standard:

Criterion A: Statutory Minimum Standard (Safety)

- 2006 Standard: Dwellings must be free of Category 1 hazards as defined by the Housing Health and Safety Rating System (HHSRS).
- New Standard: Maintains the 2006 criterion.

Criterion B: Reasonable State of Repair

- 2006 Standard: A home fails if one or more *key* building components are old and, because of their condition, need replacing or major repair; or if two or more *other* components are old or need replacing or major repair.
- New Standard: A home fails if one or more *key* building components are not in a reasonable state of repair; or two or more *other* building components are not in a reasonable state of repair.

Criterion C: Reasonably Modern Facilities and Services

- 2006 Standard: A home fails if it lacks three or more of the following: a modern kitchen (less than 20 years old), a kitchen with adequate space and layout, a modern bathroom (less than 30 years old), an appropriately located bathroom and WC, adequate insulation against external noise, and adequate size and layout of common entrance areas.
- New Standard: The age requirement of kitchens and bathrooms has been removed, but these facilities must be kept in good repair. Omitting the age requirements, flats must provide three of the facilities and services outlined in the 2006 Standard, whereas houses must provide two. All windows that present a fall risk for children must have restrictors.

Criterion D: Thermal Comfort

- 2006 Standard: Decent homes must have both efficient heating and effective insulation.
- New Standard: The primary heating system must heat the whole home and be programmable by tenants. Homes should meet Energy Performance Certificate (EPC) C, under a new reformed EPC system.

Criterion E: Damp and mould

- 2006 Standard: not mentioned explicitly separate from criterion A.
- New Standard: A home should be free of damp and mould.

This report aims to address this gap by introducing the Non-Decent Index (NDI), a publicly available index and dataset that can be used to understand variation in PRS quality between neighbourhoods and identify small areas with a high expected rate of non-decency.

The following report: outlines the methodology for constructing the NDI; validates the NDI using local authority PRS inspection data and feedback from stakeholders; demonstrates how the NDI can be used to identify hotspots of PRS non-decency; considers the potential applications of the NDI for practice and research; and discusses the NDI's implications and limitations.

Methodology

The purpose of the NDI is to identify concentrated areas, or 'hotspots', of DHS failure among private rented homes. To achieve this objective, Lower Super Output Areas (LSOAs) are treated as analogous to neighbourhoods. LSOAs are statistical geographies established to calculate and disseminate statistics for the Census. The primary benefit of treating LSOAs as neighbourhoods is the abundant data on demographic, economic and housing statistics available at the LSOA level.

To construct the NDI, I use a population disaggregation approach that is a modified form of the method outlined by Yankey et al. (2024). Population disaggregation modelling involves first using machine learning to estimate an outcome variable available for a larger administrative area. This model is subsequently used to disaggregate the outcome from the larger area to smaller areas according to the location of predictor variables within target small areas. The process produces more granular data than would otherwise be accessible.

In this case the outcome variable is the proportion of PRS homes failing the DHS, the larger areas are local authority districts, and the small areas are LSOAs. The data source for local authority districts is the *MHCLG local authority housing stock condition modelling 2023* dataset, which provides an estimate of the proportion of PRS homes failing the DHS within each English local authority. The MHCLG data is the product of a modelling exercise that uses EHS, Census, EPC and Experian data. The assumption of the NDI, therefore, is that the MHCLG model is broadly correct. This is obviously a strong assumption. In the conclusion, I reflect upon the implications of this for the NDI and future research. It is also worth highlighting that the MHCLG data, and by extension the NDI, model failure against the current DHS. As it has only recently been defined, and is not yet implemented, there is a lack of data on compliance with the updated DHS.

To perform the disaggregation, I use a stacked ensemble machine learning model. A stacked ensemble model is a machine learning architecture using two layers. The first layer consists of several different models – in this case linear regression, a general additive model (GAM), and a neural network – each of which is trained to predict the local authority district outcome. The second layer then uses the results from these various models as its own inputs to predict the outcome, with the second layer model being a GAM. This approach tends to produce more accurate predictions on new data than a single layer model, which is beneficial in the case of population disaggregation where the LSOA data is unseen by the training model. The models were trained using a wide range of data on LSOA demographics and housing, including property age, energy efficiency, tenure, heating source and property type. The local authority model was refined by testing predictions on a subset of withheld observations. The accuracy of these models was found to be very high, with a very strong correlation between the predicted values and the government estimates. Full details of the methodology and variables is available in Appendix A.

The development of the NDI followed four sequential stages:

1. The stacked ensemble model was first used to predict the percentage of PRS homes failing the DHS at the local authority level.
2. The trained model was used to predict the percentage of homes PRS failing the DHS at the LSOA level, using the same predictors in the first step but measured at the LSOA level.
3. The predictions from stage two were used as a set of weights to redistribute the local authority level DHS failures across LSOAs. This stage ensures that when reaggregated, the LSOA figures match the local authority figures.
4. The output of step 3 was weighted by the size of the PRS in an LSOA relative to the rest of England. This ensured that the NDI prioritised areas where there is both a high rate of DHS non-compliance and a significant number of private tenants
5. The results were scaled from zero to one to aid interpretation – a score of zero represents the LSOA with the lowest risk nationally, while a score of one represents the highest.

Following the construction of the NDI, the research validated the results through two steps:

- Analysing the correspondence between NDI predictions and local authority PRS inspection data provided by Leeds City Council (LCC)
- Gathering feedback from stakeholders and practitioners to understand whether the NDI predictions align with local knowledge.

Validation – Leeds City Council inspection data

The first validation involved analysing the correspondence between the NDI and local authority inspection data. LCC’s Private Sector Housing team shared data from their inspections of PRS properties. Inspections are undertaken as part of a local authority’s duties under the 2004 Housing Act to assess and rectify health and safety hazards in PRS homes. Reasons for an inspection can include a complaint, the presence of a house in multiple occupation (HMO), or the location of a property within a selective licensing scheme (see below).

The objective of this validation step is to assess whether the hotspots of DHS failure identified by the NDI align with the local knowledge of staff conducting physical inspections of properties. It is worth acknowledging the limitations to this validation step. The LCC data is not an unbiased sample of property inspections as inspections will be responsive to the receipt of complaints, which are known to be an imperfect mechanism for raising issues in the PRS due to the power imbalance between landlord and tenant (Harris and Marsh, 2022). Plus, the existing inspections regime of English local authorities is affected by the data limitations highlighted within this project. Regardless, the argument made here is that if LCC inspections identify a relatively high frequency of HHSRS hazards in areas where the NDI is also high, this is quite obviously preferable to a situation where the LCC inspections and NDI disagree, accepting the limitations inherent to the exercise. Furthermore, LCC inspections data can provide insight into the types of hazards commonly found within areas with a high NDI.

Leeds City Council (LCC) shared two datasets:

1. P1 action codes – property inspections which do not involve a full HHSRS assessment but will assess the existence of hazards and may result in an enforcement action e.g. Hazard Awareness Notice, Improvement Notice.
2. HHSRS inspections – property inspections which involve a full HHSRS assessment

Both datasets included the date of the inspection, the hazard(s) identified, the property postcode, and whether the property was in a selective licensing area. Each dataset covered all inspections from 1 April 2023 to 31 March 2025. Prior to sharing the data was pseudonymised to remove the full address and any identifying information, and each property was designated a neutral unique reference number. The HHSRS data included whether the hazard was Category 1 or 2, with all Category 1 hazards indicating a DHS failure. The P1 action code data did not include this variable, but LCC indicated that a reasonable working assumption was that all P1 hazards should be considered Category 1, with the exception of those that were designed as 'Other' under the hazard type variable. All analysis in the validation stage focused on the first inspection of each home as this is the closest approximation to a cross-sectional survey and not all properties received a repeat inspection. In total 2,250 properties received at least one inspection across both LCC datasets and 3,738 category 1 hazards were identified on first inspections.

To validate the NDI we should expect to see category 1 hazards identified through LCC inspections located in areas with relatively high NDI scores. Figure 1 shows the NDI for Leeds LSOAs in the middle panel. For comparison, the bottom panel shows the Indices of Multiple Deprivation (IMD) housing in poor condition indicator for Leeds LSOAs. As mentioned above, the IMD housing in poor condition indicator estimates the proportion of homes failing the DHS in an LSOA *irrespective of tenure*. We should therefore expect it to be correlated with the NDI, but not equivalent due to the difference in tenure focus on the weighting step included in the NDI. Figure 1's top panel visualises the spatial distribution of category 1 hazards identified on the first LCC inspection. The density of category 1 hazards is visualised through probability contours, which are calculated using a kernel density estimate. Probability contours can be interpreted as the probability a hazard will be located within a particular spatial boundary. A smaller probability represents an area of high density, or in this case a location with a very high concentration of category 1 hazards identified by LCC. In Figure 1, the 10% contour represents a boundary where if a point is selected at random, there is a 10% probability it will fall within this boundary. The 10% boundary is therefore the area with the highest density of category 1 hazards. Category 1 hazards not falling within at least the 90% probability contour are plotted as individual points in Figure 1.

Figure 1 shows the highest NDI LSOAs exist broadly in a ring around the city centre, especially in areas just bordering the northeast and southwest of the city centre, known as Harehills and Beeston, respectively. The northern part of the city centre also has many high NDI LSOAs as the PRS is the predominant tenure. Harehills and Beeston are associated with several risk factors, including a large proportion of terraced properties, built pre-1919, in EPC bands E-G. The IMD indicator in the bottom panel of Figure 1 reaffirms the high expected non-decency in Harehills and Beeston, as well as to the north of the city centre. But it also highlights several LSOAs in the north and east of the Leeds authority that have a relatively large proportion of homes in EPC bands E-G. These are, though, LSOAs where owner-occupation predominates and the PRS is a marginal tenure. Therefore, they are not areas where we should expect a high density of hazards in the LCC inspections data.

Reassuringly, the areas with the highest density of category 1 hazards tend to have a high NDI. There are areas with a low NDI where category 1 hazards have been identified, but the density of hazards in these areas is low, and this is to be expected as a low NDI does not imply the complete absence of DHS failures. Moreover, Figure 1 shows a very low density of identified hazards in areas with a high IMD indicator score but a small PRS. By contrast, the NDI has a closer resemblance to the spatial distribution of hazards identified through PRS inspections, underscoring the strengths of the NDI as a PRS specific index. As such, the initial visual inspection of the NDI and LCC inspection data suggests broad alignment between the data sources.

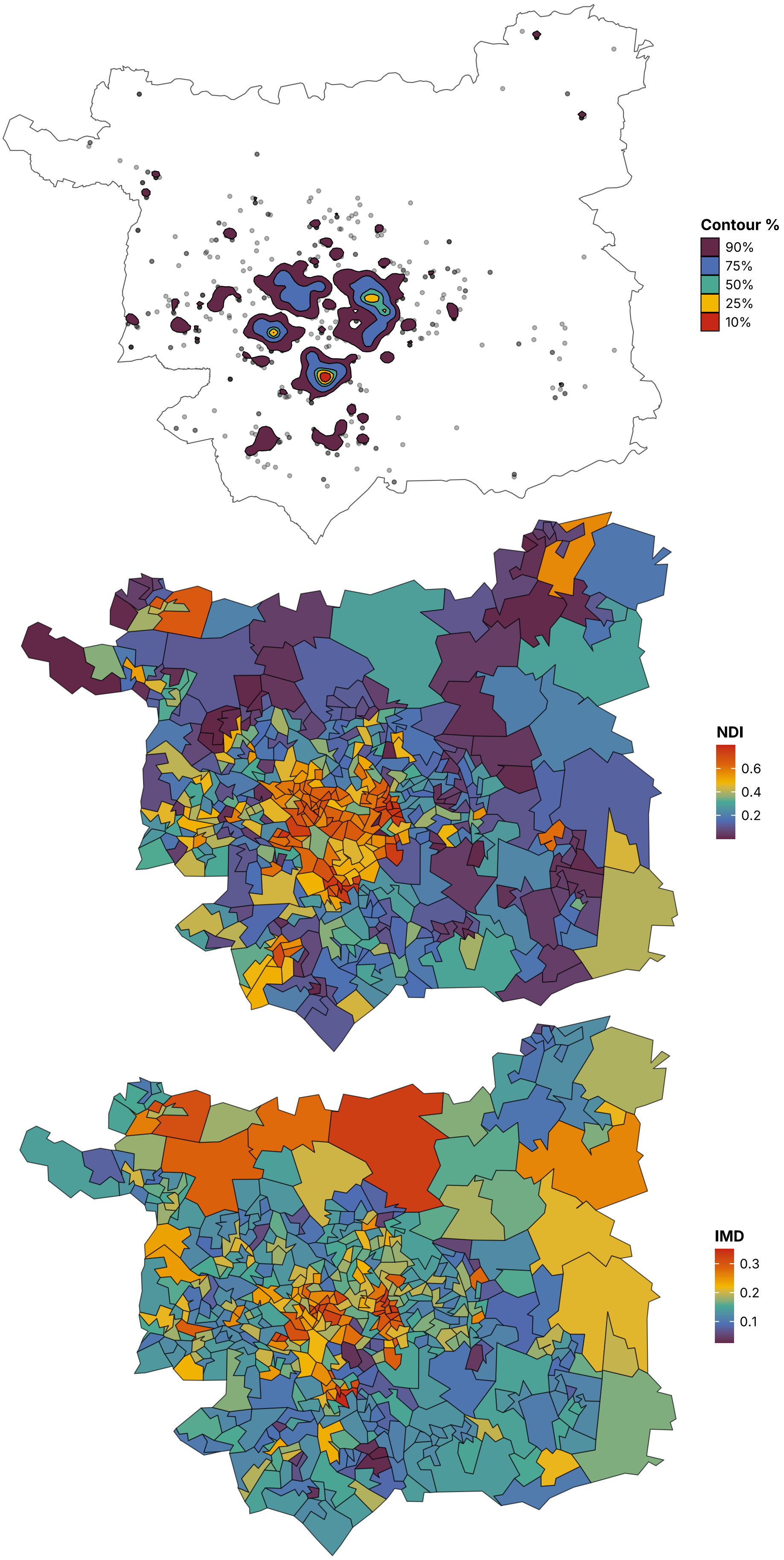

Figure 1: NDI, IMD indicator and category 1 hazards from Leeds PRS inspections

One of the reasons for a high density of inspection data in Harehills and Beeston is the existence of historic selective licensing schemes in these areas that were in effect from 6 January 2020 to 5 January 2025. A selective licensing scheme is a designation by a local authority that requires every private landlord in an area to obtain a license for their properties. Selective licensing also allows authorities to conduct a more proactive inspections regime. A selective licensing scheme must be supported and evidenced by a business case that demonstrates the existence of localised issues such as poor housing conditions, deprivation, or persistent anti-social behaviour. The Beeston and Harehills schemes licensed over 6,000 properties through their duration. LCC reporting stated that 85**%** of properties that received an inspection were not legally compliant with housing standards when first inspected and that hazards were removed from 1,430 homes.[1] Figure 2 shows the location of category 1 hazards identified by LCC on the first inspection, with points coloured by whether a property was in a historic selective licensing scheme, indicating the location of the Harehills and Beeston historic schemes.

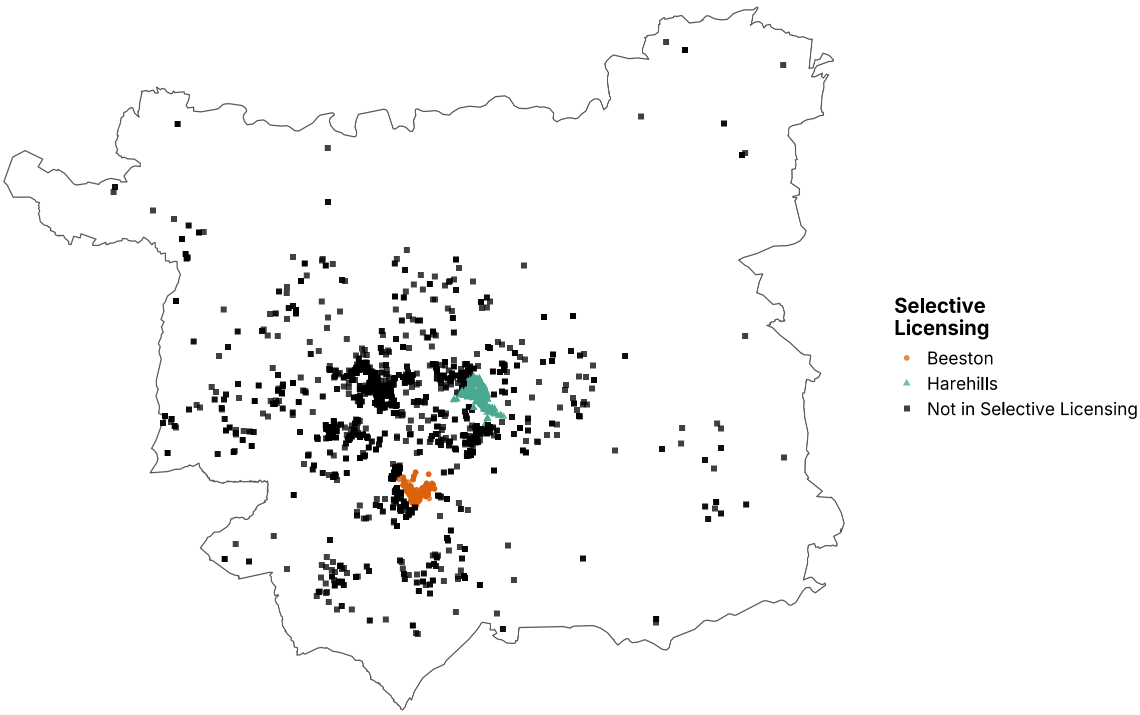

Figure 2: Category 1 hazards in Leeds by historic selective licensing scheme

[1] The efficacy of PRS inspections is not the focus of this report and so the outcomes of inspections are not reported in depth. However, initial exploratory analysis does support the notion that inspections tend to be followed by a reduction in hazards. Among PRS properties in Leeds that received multiple inspections, the average HHSRS score fell from 2,464 on the first visit to 171 on the second. Further research would be required to see if this finding generalised to properties receiving only a single inspection.

Both Beeston and Harehills are distinctive due to continued presence of back-to-back terraced properties (Harrison, 2017). Back-to-backs will be treated as indistinguishable from general terraced houses in the NDI as this is how they are treated in the Census. Consequently, there are certain property archetypes with a high propensity for DHS failure which may be hard for the NDI to identify with the available data. Yet despite this nuance, Table 1 shows the average NDI of LSOAs containing at least one historic selective licensing property is higher than the average NDI in non-selective licensing areas.

Area	NDI
Beeston	0.638
Harehills	0.594
Not in selective licensing	0.281

Table 1: NDI scores by historic selective licensing schemes in Leeds

Table 2 summarises the types of Category 1 hazards identified by LCC on the first inspection of homes within its historic selective licensing schemes (i.e. Beeston and Harehills). The most common hazards related to fire safety, fall concerns, and damp and mould.

Hazard	Percentage
Fire safety	27.26
Fall Concerns	21.14
Damp and mould growth	16.37
Excess cold	15.45
Electrical hazards	11.54
Crowding and space	5.20
Entry by intruders	2.71
Other	0.33

Table 2: Category 1 HHSRS hazards identified in historic selective licensing areas in Leeds (1 April 2023-31 March 2025)

In Leeds a new expanded selective licensing scheme began on 9 February 2026. Figure 3 shows the NDI with the area for the new selective licensing scheme overlaid. The LCC justification for the extended scheme in their business case was based on improving conditions in the PRS and reducing deprivation. The evidence compiled several risk factors associated with the homes in the licensing area, including:

- 46.8% of homes being terraced properties, compared to 25% city wide
- 37.7% of households being in the PRS, compared to 21.8% city wide
- 27% of households experiencing fuel poverty in 2022.

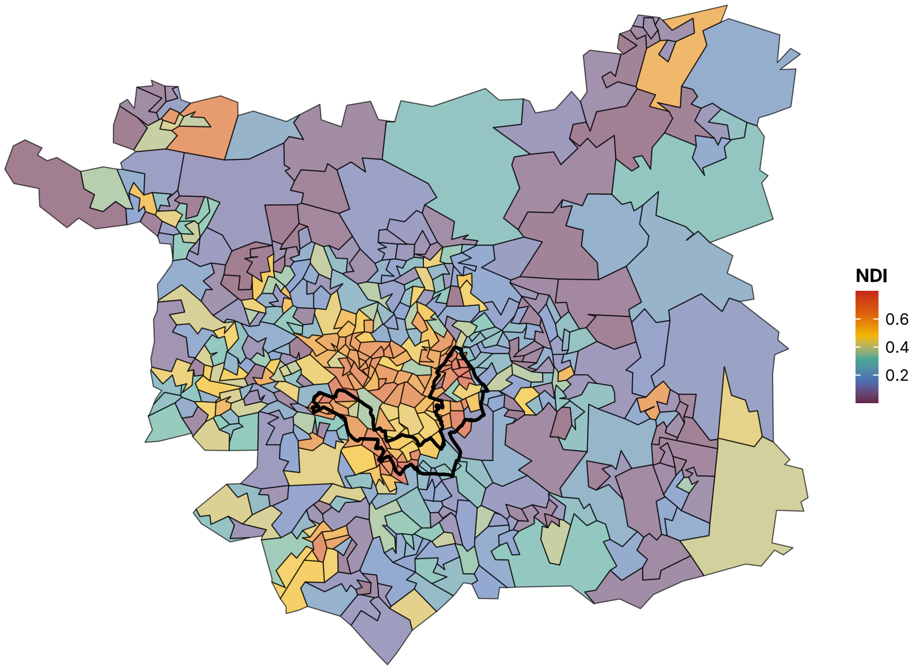

Figure 3: NDI and new selective licensing scheme in Leeds

Figure 3 shows that while the new selective licensing scheme wholly contains some LSOAs, it intersects with only small fractions of others. As such, Table 3 compares the NDI between LSOAs inside and outside the licensing scheme, but the NDI score in Table 3 is a weighted mean that weights the index by the percentage of an LSOA's area that intersects with the licensing scheme. Table 3 again shows a higher NDI for the selective licensing scheme LSOAs compared to those outside the scheme.

Area	NDI
Selective licensing	0.584
Not in selective licensing	0.268

Table 3: Weighted NDI scores by new selective licensing scheme in Leeds

Accepting the caveat that the LCC data is not an unbiased sample, the correspondence between the NDI and LCC selective licensing schemes is taken as a positive indication of the validity of the NDI. This is on the basis that property inspections undertaken by LCC of licensed properties have found a high frequency of DHS failures historically. The LCC business case for the current selective licensing scheme also relied upon several risk factors that mirror the predictors of high NDI scores, including property type, tenure and fuel poverty (which will be related to property energy efficiency). This suggests the NDI is capturing the risk factors recognised by practitioners as pertinent to non-decency.

Validation – stakeholder feedback

A webinar was held in February 2026 where stakeholders provided feedback on interim findings from the project. 48 stakeholders attended the webinar, including tenants, local authority employees, social landlords, researchers and civil servants. The webinar shared the NDI and invited feedback on whether the index was identifying variation between LSOAs in housing quality based upon the knowledge of attendees, for instance knowledge gathered through their employment or research.

Feedback from the webinar was positive, with several attendees reporting that the NDI was well aligned with their local knowledge and experience. Consequently, feedback from the webinar did not result in any further amendments to the NDI methodology.

Rather, much of the discussion focused on understanding the process of validating the NDI, the potential applications of the NDI, and how to most effectively disseminate the findings. Attendees suggested the NDI could be used for strategy and policy development, building partnerships, targeting interventions to address hazards, and evidencing the case for selective licensing. Attendees also suggested that NDI users would benefit from the provision of an interactive tool allowing them to navigate between neighbourhoods and visualise the NDI (see Executive Summary and Conclusion).

Hotspots of non-decency

The NDI is intended as a tool to identify hotspots of non-decent PRS housing and housing quality issues. Depending on the interests of the user, it can be used at a national, regional or local scale to identify clusters of non-decent PRS homes. The reasons why poor-quality housing concentrates in certain areas will be context and historically specific, and an exhaustive analysis of the various archetypes of poor-quality housing existing across England is beyond the scope of this report. The preceding analysis of Leeds has highlighted the case of back-to-back terraced houses in Beeston and Harehills. While Beeston and Harehills have relatively high NDI scores, it would require additional data and analysis to distinguish LSOAs containing back-to-backs from LSOAs with a high NDI generally, or to determine the likelihood a back-to-back fails the DHS. Such granular analysis, by either practitioners or researchers, remains most appropriate at the local level (see Harrison, 2017).

However, the NDI can support such analysis by helping focus attention and directing the search for hotspots of PRS non-decent housing. Initial exploratory analysis using archetypal areas with high NDI scores is provided below, although this list is not exhaustive. Note that in the examples that follow the colour scale ranges from the lowest to highest NDI score nationally, whereas the visualisations for Leeds above vary from the lowest to highest index scores within Leeds only.

The first archetype is illustrated using the Sheffield local authority. Figure 4 shows that the highest NDI scores in Sheffield are found in the urban city centre and to the east of the city. Both areas have a large PRS that consists of a mix of mostly flats and terraced housing. Yet, while the city centre accommodates most of Sheffield's student population, the east of the city is a more deprived area that accommodates many lower-income households and households with members born outside of the UK.[2]

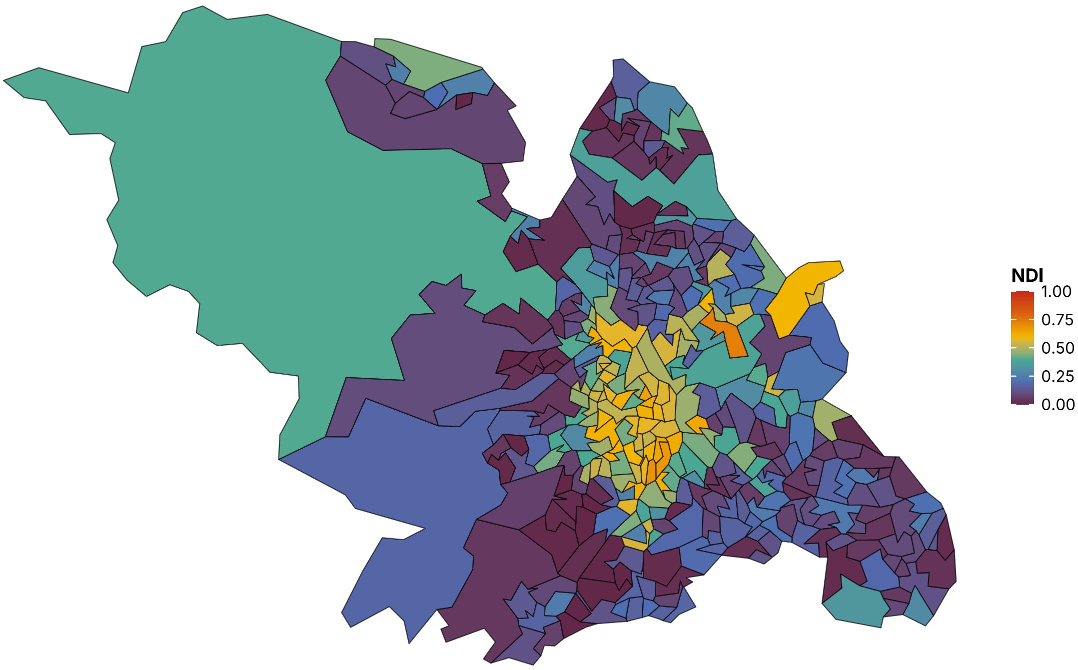

Figure 4: NDI in Sheffield

[2] I use the term 'born outside of the UK' as this reflects the terminology used in the 2021 Census table on Country of Birth, which is used in the analysis (see Appendix). It is worth noting that place of birth is not a proxy for nationality or migration status; many individuals in this category are British citizens or have been long-term residents. Moreover, they may be resident in a household with someone born in the UK.

The second case study local authority is Kirklees, displayed in Figure 5. The PRS in Huddersfield town – the largest urban area in Kirklees – includes a relatively high proportion of terraced homes, built pre-1919, in EPC bands E-G. In the highest NDI LSOAs in Kirklees, as many as 44% of the properties are in EPC bands E-G, compared to a national average of 16.5%. Furthermore, in the areas of Kirklees with the highest NDI one in twenty households lacks central heating. Collectively, Leeds, Sheffield and Kirklees illustrate that in many urban areas of England the PRS has become spatially concentrated around neighbourhoods of older, terraced housing with poor thermal efficiency.

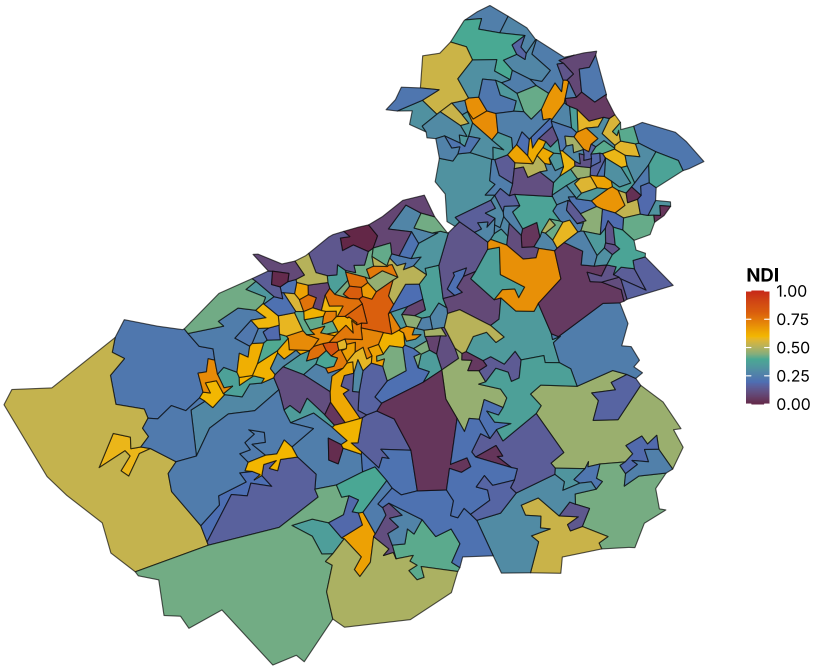

Figure 5: NDI in Kirklees

Poor quality PRS housing is not exclusively an urban issue. While it is true that the majority of the English PRS stock is in urban areas, some of the poorest condition PRS housing is within rural areas. Rural areas face distinct challenges in improving the condition of their housing stock. Many rural properties are older and hard to retrofit, with persistent energy efficiency challenges. They are also sparsely located which makes it harder to derive economies of scale from area-based programmes of housing improvement. In addition, PRS properties that are off the gas-grid and reliant upon solid fuel heating are more common in rural areas (Stewart and Bolton, 2024). Figure 6 illustrates with Northumberland, which has several former mining areas where many households remain reliant upon solid fuel for heating, and consequently the highest NDI scores in Northumberland are within more sparsely populated areas in contrast to the lower NDI in urban areas bordering Newcastle Upon Tyne.

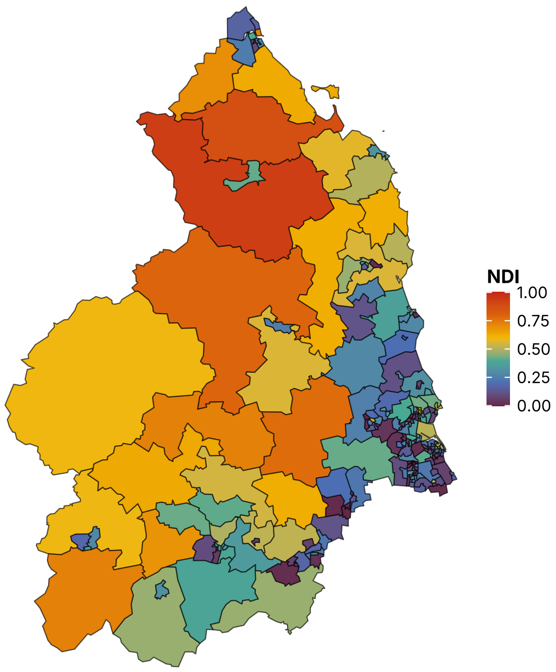

Figure 6: NDI in Northumberland

Potential applications of the NDI: Practice

For practitioners, the NDI is most appropriately used as a tool to inform strategy and to direct resources, communications and attention as the DHS is implemented in the PRS. This section of the report outlines suggestive uses for the NDI based upon feedback from stakeholders involved in the research and webinar attendees.

Targeting communications with landlords and tenants ahead of the implementation of the DHS in the PRS. Previous research has found that PRS landlords value and welcome proactive communication regarding regulatory change (Harris and Marsh, 2022). The NDI could be used to target communications ahead of the implementation of the DHS in the PRS. While the national landlord database introduced by the Renters' Rights Act will increase transparency over the location of PRS properties, the NDI could provide evidence on where more intensive communications are required, for example follow-up reminders or in-person visits.

Targeting local authority inspections in the PRS. The NDI provides a tool to understand where both a high volume of HHSRS hazards and tenant complaints should be expected. In the context of scarce resources and increased demand, local authorities could use the NDI to help target inspections and enforcement activity.

Evidencing the need for place-based interventions. By identifying areas where housing needs long-term investment or regulatory intervention, the NDI could be used to evidence the need for place-based interventions that aim to improve housing quality. Such interventions could include selective licensing schemes or estate refurbishment and regeneration.

Nonetheless, it is worth reiterating for potential users that as a spatial tool focused on LSOAs, a high NDI does not imply that all homes within the area fail the DHS. Nor does it imply that all the homes in an LSOA with a low NDI are compliant. Indeed, there will be large numbers of non-decent homes located in areas with a low NDI.

Potential applications of the NDI: Research

In addition to acting as a tool for practitioners, the NDI may have applications within research. The section below provides an illustrative example by using the NDI to identify and analyse rental submarkets.

Figures 7 and 8 illustrate how the NDI can be used to delineate and analyse rental submarkets using Leeds as a case study. Figure 7 categorises LSOAs according to their rental submarket, which was identified using the k-means algorithm to categorise LSOAs according to their NDI and rental price. A rental price index was constructed using 2022 Zoopla data for this purpose (see Appendix B for full details). Figure 7 also shows two panels which identify spatial autocorrelation in rental prices (bottom-right panel) and the NDI (top-right panel). The submarket analysis suggests that high rental prices tend to cluster in the north of the Leeds authority and the city centre, whereas high NDI LSOAs cluster in the city centre and the areas subject to selective licensing discussed above (i.e. Beeston, Harehills). This results in three submarkets:

- *High NDI / High Price*: located in the city centre in LSOAs accommodating mostly working age households, young professionals and students
- *High NDI / Low Price*: located adjacent to city centre in mostly older terraced housing, with an above average population of people born outside of the UK
- *Low NDI / Average Price*: LSOAs where most of the homes are expected to comply with DHS and the PRS is a minority tenure

Figure 8 displays the average rental price over time per submarket in Leeds. The data is taken from Zoopla rental listings between September 2014 and December 2022. The solid lines display the arithmetic mean for each monthly interval and the dashed line the smoothed price trend. There are not only clear price differentials between submarkets, but they also endure over time. There is little to no convergence between submarkets, despite the price index in Figure 7 relying solely on 2022 data. Moreover, the submarkets experience contrasting seasonal trends, with the large proportion of students in the *High NDI / High Price* submarket producing large seasonal fluctuations associated with the beginning of the academic year.

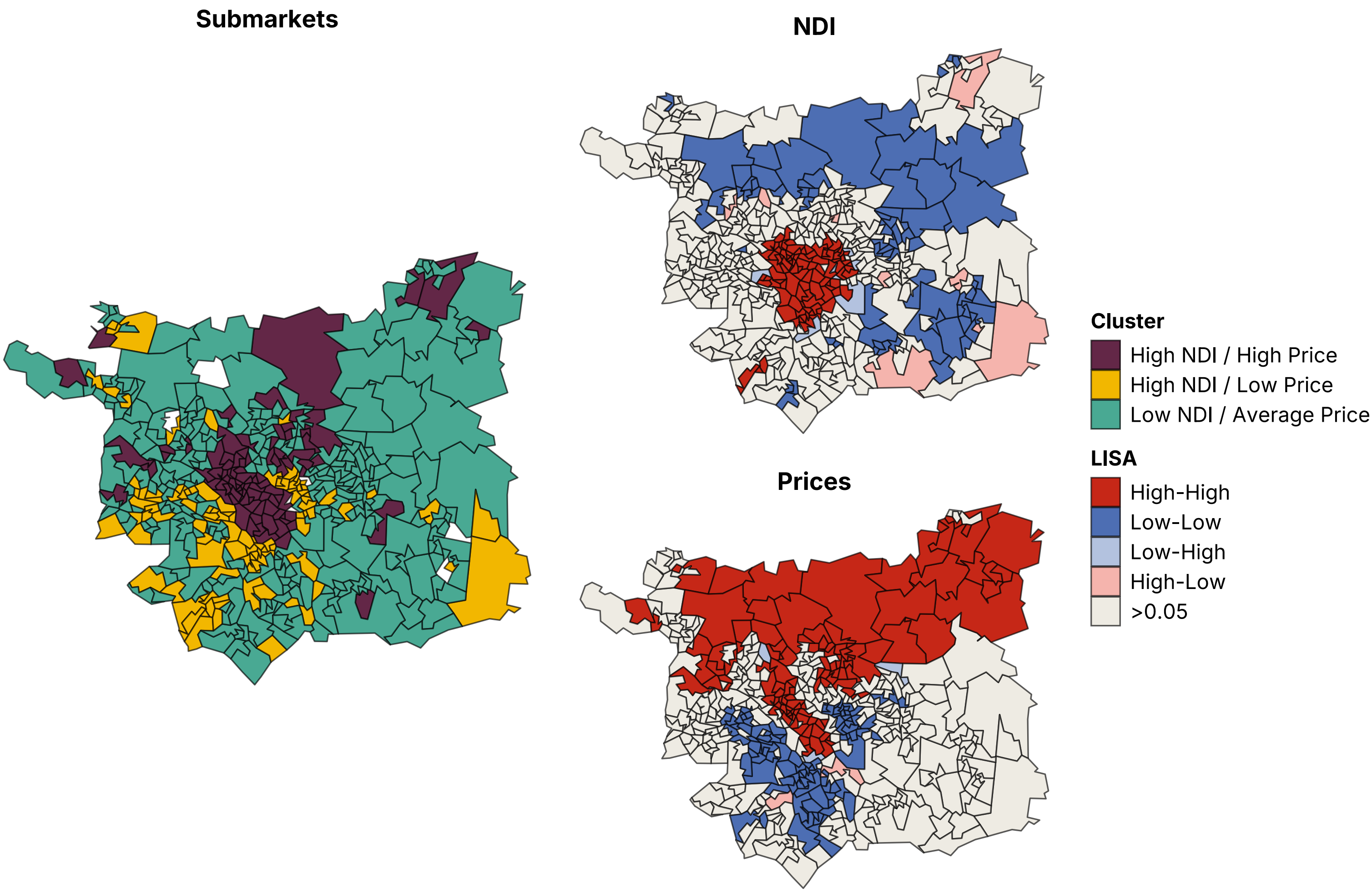

Figure 7: Leeds rental submarkets and spatial autocorrelation in the NDI and rents

The analysis of Leeds displayed in this report is purely illustrative and further research could seek to use the NDI to improve our understanding of rental submarkets. One area of inquiry could be to analyse the location of amenities that distort the housing market and drive demand in areas of low housing quality. The location of universities is likely to be a case in point, as illustrated by Figure 8, but there are undoubtedly many others.

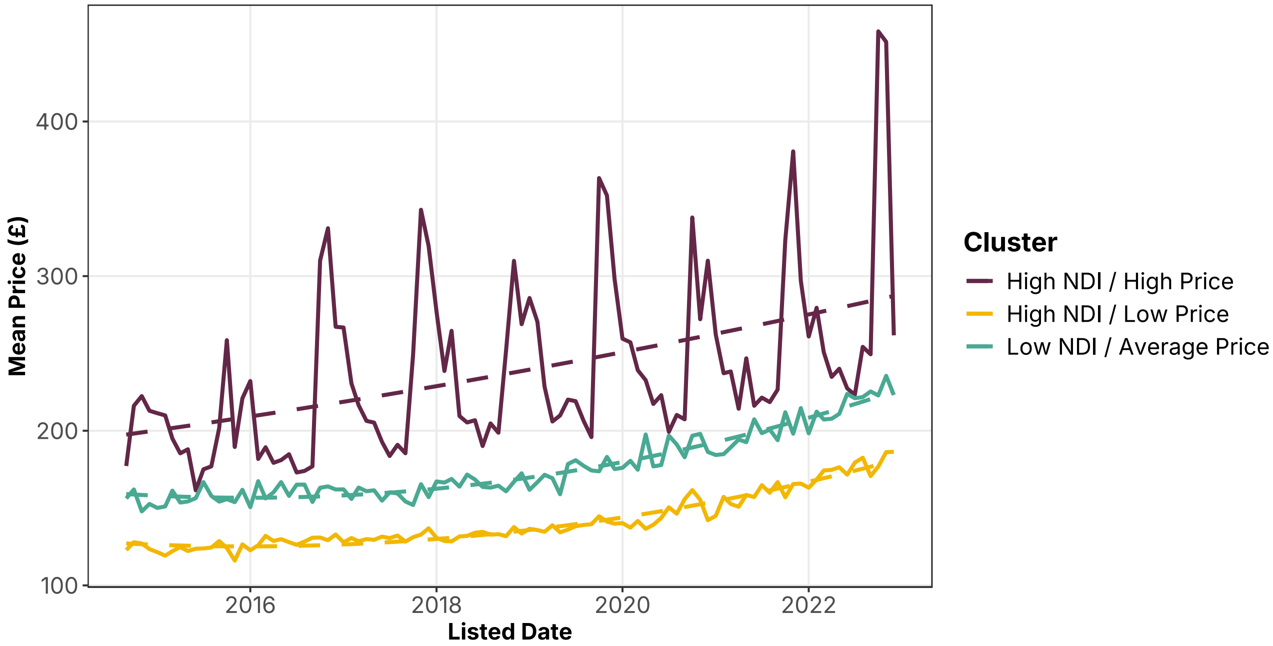

Figure 8: Average rental prices by submarket in Leeds 2014-2022
Data source: Zoopla.

Limitations

Although the NDI represents an advancement in understanding the spatial distribution of DHS non-compliance in the PRS, it has some limitations. The primary limitation is that it assumes the MHCLG data on local authority DHS compliance is broadly correct. The validation steps taken suggest that the NDI is capturing meaningful variation between LSOAs in DHS compliance. Nonetheless, this assumption will introduce some unavoidable error. Consequently, the current NDI should be seen as analogous to a beta version of a software product. There is inevitably some error within the NDI but in its current format it provides a useful strategic resource for users. And releasing the NDI allows for user feedback to inform improvements in future iterations.

The principal constraint on further improvements is the sample size of national surveys that conduct property inspections e.g. EHS. The usage of the MHCLG data is a pragmatic solution in the absence of more granular primary data, but the NDI is likely as accurate as can be expected given the constraints of relying solely on a desktop exercise. Future research could use primary data collection and property surveys to validate and refine the NDI. And NDI user testimony could provide a valuable resource in compiling the business case for such research.

The second limitation is that the NDI is a snapshot in time given it relies upon 2023 MHCLG estimates and 2021 Census data. As mentioned above, the NDI is most appropriately used as a strategic tool by practitioners and as a tool to analyse variation between LSOAs by researchers. It should not be used by practitioners as a live tool to monitor improvement over time or to evaluate improvement resulting from targeted interventions (although it could be used to inform the case for such an intervention). Similarly, it should not be used by researchers to analyse change within LSOAs over time.

The third limitation is that the NDI cannot disaggregate into individual DHS criteria. For instance, it does not capture what proportion of PRS homes in an LSOA fail the thermal comfort criterion or what proportion fail the state of repair criterion. Given the importance of the EPC data to the model, then it is reasonable to assume the NDI is an effective proxy for areas where a significant proportion of PRS homes will fail the thermal comfort criterion. However, it is at best a proxy for these outcomes rather than a direct measure. Finally, the NDI focuses on the current DHS and does not model hotspots of failure for the updated DHS due to come into effect in 2035. There is currently insufficient data on the factors associated with non-compliance with the updated DHS, and existing forecasts on the number of homes that may fail are inherently uncertain. As data becomes available, for example through future iterations of the EHS, the NDI could potentially be modified to include the updated DHS. But as there remains significant overlap between the current and updated DHS (see Box 1), a high NDI represents a good proxy for LSOAs where a high proportion of PRS homes are expected to fail an updated DHS. Therefore, the NDI remains a useful strategic tool to prepare for implementation of an updated DHS.

Conclusion

This report has introduced the NDI, a publicly available tool that identifies LSOAs where a relatively high number of PRS homes are expected to fail the DHS. Access to the NDI dataset can be found at this repository. And users can visualise the NDI within individual local authorities using a purpose-built application.

The NDI was constructed using a population disaggregation method that utilises machine learning to estimate the proportion of PRS homes in an LSOA that fail the current DHS. Model predictions were subsequently weighted according to the relative size of an LSOA's PRS. The validation checks suggest areas with a high rate of category 1 HHSRS hazards, according to local authority inspection data, tend to have a high NDI, giving confidence as to the accuracy and utility of the NDI.

The research has underscored the potential for a strengthened DHS within the social and private rented sectors to transform the quality of English housing and to promote healthier and more sustainable homes. The LCC inspection data and historic selective licensing schemes illustrated the high rates of regulatory non-compliance that can exist within the PRS, but also the potential for targeted place-based interventions to improve standards. One of the objectives of the NDI is to support these interventions by providing a tool that can efficiently direct resources and activity.

Finally, the analysis of hotspots of non-decency has demonstrated that areas with a high NDI are heterogeneous – they are in both urban and rural areas, and neighbourhoods of both high and low rental prices. The measurement and analysis of housing quality, therefore, represents a useful research endeavour that helps paint a more vivid picture of local housing systems. Nevertheless, further research is required to improve and refine the

NDI. As mentioned above, the current iteration of the NDI should be seen as analogous to a beta product that is somewhat limited by the reliance upon secondary data sources. But more fundamentally, as with any measurement tool, the NDI is hopefully a tool for further research that can diagnose the causes of variation between places in housing quality and support effective interventions.

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Appendix A: NDI Construction Methodology

The NDI is constructed using a process of population disaggregation that is a modified version of the method outlined by Yankey et al. (2024). Population disaggregation begins with an outcome measured at a higher spatial scale and uses machine learning to disaggregate it to small areas, consequently producing more granular data. Yankey et al. (2024) use Bayesian Additive Regression Trees (BART) to disaggregate population estimates at the district level to target grid cells. By contrast, I modify this framework by using a stacked ensemble machine learning model rather than BART, and LSOAs as the target small area rather than grid cells.

My intended outcome is the percentage of PRS properties failing the DHS in an LSOA, which I disaggregate from the percentage of PRS homes failing the DHS at the local authority district level. The data source for local authorities is the *MHCLG local authority housing stock condition modelling 2023*. The MHCLG data is the product of a modelling exercise that uses EHS, Census, EPC and Experian data.

A stacked ensemble model is a machine learning architecture that has two layers. The lower layer is a diverse set of different models that are trained to predict the outcome. The top layer uses the predictions from the lower layer models as predictor variables which helps capture complex patterns that individual models might miss. As such, it produces models that tend to generalise more accurately to unseen data. I train the ensemble using the *caret* package in R (Kuhn, 2008). I use five-folds cross-validation to tune the model hyperparameters. I hold-out 20% of observations as a test dataset. And I choose between competing models based upon the root mean squared error (RMSE) statistic on the test dataset.

The ensemble model lower layer consists of an ordinary least squares regression, a general additive model (GAM), and a feed-forward neural network. The top layer is a GAM. The predictors for the lower layer models are outlined in Table A1. The property age variable had missing values due to the CDRC data being based upon 2011 LSOAs rather than 2021 LSOAs. Missing values were imputed using the random forest algorithm (see Marshall, 2024).

The construction of the NDI proceeded through the following stages:

1. Model the percentage of PRS homes failing the DHS at the local authority district level – where y_j denotes the modelled outcome for the jth local authority – using the stacked ensemble machine learning model.
2. Use the model from stage one to predict the modelled percentage of PRS homes failing the DHS at the LSOA level, where $\hat{y}_i$ is the model's predicted outcome for the ith LSOA. The same predictors are used at stage two as stage one but measured at the LSOA level e.g. the percentage of owner-occupiers in the LSOA, the percentage of properties with an EPC F/G in the LSOA etc.

Variable	Source
Retirement status	Census 2021
Percentage of population retired	
National Statistics Socio-Economic Classification	Census 2021
Percentage of population in higher managerial or professional occupations	
Percentage of population in lower managerial occupations	
Percentage of population in semi-routine occupations	
Percentage of population long-term unemployed or never employed	
Percentage of population full-time students	
Household tenure	Census 2021
Percentage of households in owner-occupation	
Percentage of households in PRS	
Primary heating source	Census 2021
Percentage of homes with electric heating only	
Percentage of homes with fixed room, wood, or solid fuel heating only	
Property type	Census 2021
Percentage of households in semi-detached housing	
Percentage of households in terraced housing	
Country of birth	Census 2021
Percentage of population born in Middle Eastern or Asian country	
Energy Performance Certificate (EPC)	DLUHC Open Data
Percentage of homes at EPC band E	
Percentage of homes at EPC bands F or G	
Property age	Consumer Data Research Centre
Percentage of homes constructed pre-1919	
Percentage of homes constructed 1919-1944	
Percentage of homes constructed 1945-1990	
Region	

Table A1: Variables used for constructing the Non-Decent Index

3. Use the modelled predictions from stage two to disaggregate the number of local authority DHS failures across LSOAs. To do so:
   a. the model's predicted percentage of PRS DHS failures per LSOA is multiplied by the total number of PRS households in the LSOA to estimate the total number of LSOA failures, where $PRS\_households_i$ is the number of PRS households for the ith LSOA, and $\widehat{DHS}_i$ is the modelled number of total DHS failures in the PRS:

$$\widehat{DHS}_i = \hat{y}_i \times PRS\_households_i$$

b. The modelled number of total LSOA DHS failures in the PRS is divided by the sum of the modelled total across all LSOAs within the local authority district, where $\sum_{i=1}^{n} \widehat{DHS}_i$ is the sum of modelled total across LSOAs, and n is the number of LSOAs within the local authority district. This produces a weight per LSOA denoted as w_i:

$$w_i = \frac{\widehat{DHS}_i}{\sum_{i=1}^{n} \widehat{DHS}_i}$$

c. The LSOA weight is multiplied by the total number of non-decent homes in the PRS in the local authority district, according to the MHCLG dataset. Where DHS_j is the total number of DHS failures in the PRS in the jth local authority, and $\widehat{ND}_i$ is the estimated number of non-decent PRS homes in the ith LSOA, disaggregated from the jth local authority:

$$\widehat{ND}_i = w_i \times DHS_j$$

On first reading this stage may seem duplicative, as both $\widehat{DHS}_i$ and $\widehat{ND}_i$ provide an estimate of the number of non-decent PRS homes in the ith LSOA. However, the justification is that $\widehat{ND}_i$ is constrained to the number of DHS failures at the local authority level, such that the sum of $\widehat{ND}_i$ across all LSOAs within the jth local authority is equal to DHS_j. This leads directly to sub-step d) within stage three.

d. Divide the estimated number of non-decent PRS homes by the total number of PRS households, to estimate the percentage of non-decent PRS homes, where $\widehat{ND\_PCT}_i$ is the estimated percentage of non-decent PRS homes in the ith LSOA:

$$\widehat{ND\_PCT}_i = \frac{\widehat{ND}_i}{PRS\_households_i}$$

4. Weight the output of stage three according to the size of the LSOA's PRS nationally, where $PRS_{quantile}$ is the quantile rank of the ith LSOA in terms of the size of its PRS nationally, and the NDI_i is the NDI for the ith LSOA:

$$NDI_i = \widehat{ND\_PCT}_i \times PRS_{quantile}$$

For ease of interpretation, the NDI is scaled to range from 0 to 1. As such, an index score of 0 or 1 does not indicate that 0% or 100% of the PRS properties in an LSOA fail the DHS, respectively. Rather, 0 indicates the LSOA with the lowest index score nationally, and 1 indicates the LSOA with the highest index score nationally.

The stacked ensemble model in stage one has a very high predictive accuracy. The R^2 goodness-of-fit statistic is 0.941. Usually, such a high R^2 would be a cause for concern suggesting overfitting. But in this case, it is understandable as the MHCLG outcome data is itself a model built using similar data sources and therefore we know, and can approximate, the data generating process. As such, the high R^2 is a positive indicator. Furthermore, the RMSE on the test data is 1.40 indicating that the typical magnitude of the prediction error is 1.40 percentage points. The correlation between the ensemble predictions and the test outcome is 0.980.

As a test of the fidelity of the disaggregation from local authorities to LSOAs, I reaggregate the predicted number of DHS failures per LSOA to the local authority level and calculate its correlation with the MHCLG estimate. As such, I use the output from stage 3a in the methodology section above ($\widehat{DHS}_i$) reaggregated to the local authority, rather than $\widehat{ND}_i$. This is because $\widehat{ND}_i$ is by design constrained to the local authority level and will therefore have a perfect correlation with the MHCLG estimate. The correlation coefficient following reaggregation is 0.924 suggesting a high degree of fidelity between the disaggregated data and the MHCLG local authority estimates.

This final weighting step in the NDI is common in sector-specific indices (e.g. Cantellow et al., 2026). Without this weighting step the NDI could produce results that are misaligned with the goal of identifying ‘hotspots’ of DHS failure. For instance, it could assign a high index score to LSOAs where the total size of the PRS is comparatively small. By contrast, as constructed the NDI ensures that the index is prioritising areas where there is both a sizeable PRS and high rate of DHS failures, which is more meaningful for stakeholders seeking to use the NDI for resourcing and communications.

Appendix B: Leeds Submarket Analysis

The identification and analysis of private rental submarkets in Leeds local authority proceeded through two stages. The first stage was to construct a hedonic price model to predict the natural logarithm of private rental prices. The model was a nested multilevel model with two levels consisting of individual rental listings at level one, nested within lower super output areas (LSOAs) at level two. The model specified random intercepts for each LSOA at level two and fixed effects at level one for a property listing's number of bedrooms, the number of bedroom's squared, and the month the property was listed online for rent. The number of bedrooms was mean centred. Month was treated as a factor variable with January the baseline category. Table A2 presents the regression results.

The dataset was Zoopla rental listings in Leeds throughout 2022, taken from the WhenFresh/Zoopla safeguarded dataset provided by the Consumer Data Research Centre (CDRC).[3] To remove the effect of outliers, properties listed at a price below £25 or above £1,295 were removed, representing the 0.001 and 0.999 quantile, respectively. Table A2 displays the regression table from the hedonic model.

The second stage involved using the k-means clustering algorithm to categorise LSOAs into broader submarkets. I used two variables to produce the k-means clusters: the NDI for each LSOA, and the random effect for each LSOA taken from the hedonic price model. The random effect represents the deviation in price for each LSOA from the global average, for a property of average size listed in January. The k-means algorithm identifies clusters of observations by minimising the sum of squared distances between each data point and its assigned cluster centroid. The researcher must specify the number of clusters (k) in advance and the cluster assignment is sensitive to the ordering of observations (Hincks et al., 2025). As such, I use the NbClust algorithm and the application of majority rule to determine the number of clusters (Charrad et al., 2014). I run NbClust 200 times with the ordering of observations randomised for each iteration. This results in $k = 3$.

Figures 7 and 8 in the main report present the final clusters and their price trends over time. The spatial autocorrelation in the NDI and Zoopla rental prices in Figure 7 was calculated using local Moran's I and the *spdep* R package (Bivand, 2022).

[3] Control of the WhenFresh/Zoopla data has now been transferred to the Healthy and Sustainable Places Data Service. But was initially accessed via the CDRC prior to the end of its funding period.

	Coefficient	Std. Error
Intercept	5.277 ***	(0.011)
Bedrooms	30.374 ***	(0.236)
Bedrooms^2	-3.299 ***	(0.204)
February	0.030 *	(0.012)
March	0.047 ***	(0.011)
April	0.053 ***	(0.012)
May	0.033 **	(0.012)
June	0.036 **	(0.012)
July	0.069 ***	(0.012)
August	0.088 ***	(0.012)
September	0.071 ***	(0.012)
October	0.127 ***	(0.011)
November	0.190 ***	(0.010)
December	0.087 ***	(0.013)
N	7147	
N LSOA	478	
σ^2	0.035	
τ_{00} LSOA	0.020	
AIC	-2743.333	
R^2 (fixed)	0.725	
R^2 (total)	0.825	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A2: Hedonic price model results