Technical appendices for TRSE Tool V3: **Measuring access, vulnerability, and TRSE in local areas of England**

May 2025

Appendix 1: Measuring vulnerability to social exclusion in local areas of England

Appendix 2: Measuring access to everyday destinations in local areas of England

Appendix 3: Measuring TRSE using access and vulnerability

Appendix 1: Measuring vulnerability to social exclusion in local areas of England in TRSE Tool V3

Background

TfN's TRSE tool combines access analysis and vulnerability analysis to estimate the risk of social exclusion caused by transport issues. The vulnerability analysis in TRSE tool V2 used outputs from the 2019 English Indices of Deprivation (IMD). We adopted this measure because, at the time, it was the most widely used means of measuring relative deprivation in England, and had widespread uptake by users of the tool. However, for TRSE tool V3 we have developed a new bespoke index of vulnerability.

The following factors have influenced our decision to develop this new index for V3:

1. The IMD has not been updated since 2019, and draws in part on datasets from the 2011 Census. The schedule for the next update to the IMD has not been confirmed, and at the time of writing, the results of the methodological consultation for the next IMD have not yet been published. Consequently, there is a high degree of uncertainty over the future of this metric – both in specification and frequency.

2. Even if the IMD were updated in 2024, it typically has a four-year development cycle. This reduces the potential for regular updates to the TRSE tool, something which is particularly significant as we are now able to update the access analysis component of the TRSE tool every two years, rather than relying on updates to DfT's Journey Time Statistics datasets as in V2.

3. Deprivation, as measured by the IMD, and vulnerability to social exclusion are closely related but somewhat separate concepts, and the IMD was not designed with transport-related social exclusion in mind. Moving away from the IMD therefore offers us an opportunity to better reflect the significant primary research evidence base TfN holds on the determinants of TRSE.

4. Previous releases of the IMD have grouped data by Census lower-layer super output areas (LSOAs). Our new access analysis is capable of producing metrics at the output area (OA) level, and therefore significantly improves the spatial resolution of the TRSE tool in V3.

5. The domains of deprivation within the IMD are highly correlated, and therefore do not provide an entirely satisfactory means of assessing different elements of TRSE vulnerability. V2 matched the IMD domains to destinations (for example, access to healthcare destinations with levels of health deprivation), however there is little difference between domains in most LSOAs.

Based on these factors, we have developed a new TRSE vulnerability index for V3, which we combine with new access data to estimate TRSE risk across England. Through this, we have produced a metric with a more predictable update schedule and a finer level of spatial detail, and which is shaped by our research on TRSE.

Defining vulnerability to social exclusion

Our objective is to estimate the presence of population characteristics that mean that transport issues are more likely to result in social exclusion. Underlying this is evidence that a given transport issue can have vastly different consequences for different population groups. The framework we have developed segments this into three broad elements: (1) greater constraints on transport choices, (2) greater consequences when journeys go wrong, and (3) greater needs to travel in ways that differ from peak commuter patterns. Our research shows that the following population groups are particularly likely to face additional constraints, consequences, and needs, and therefore have higher levels of vulnerability to TRSE:

1. Low household income

- **Constraints:** A lesser ability to afford the transport options available, and to seek out alternatives to cope with transport problems.
- **Consequences:** Having little or no spare financial resources to cope with unexpected transport spending, and facing the risk of debt or the inability to afford basic needs in response to unexpected transport spending.
- **Needs:** Needing to take multiple local trips to buy basic essentials at the lowest cost (for example, visiting multiple local shops rather than a single supermarket).
- **Extent of impact:** Our research indicates that most of those with a low household income face a higher risk of TRSE. This is likely to be greatest for those working, due to the costs associated with commuting, however the effect is near-universal.

2. Insecure work

- **Constraints:** A lesser ability to use cheaper, longer term public transport fares (for example, season tickets), due to irregular commuting times and locations. A lesser ability to plan journeys well in advance due to uncertainty over working hours.
- **Consequences:** A loss of pay or loss of work as a result of minor transport problems, linked to a lack of defined working hours and a lack of job security.
- **Needs:** The need to travel for multiple part time jobs, and to travel to a range of peripheral locations (for example industrial areas on the outskirts of cities).
- **Extent of impact:** Insecure work does not always increase the risk of TRSE. Many self-employed people have variable earnings and places of work, without a higher risk of TRSE. The population group most likely to be affected are part-time workers with insecure working conditions in low-income households.

3. Caring responsibilities

- **Constraints:** Greater likelihood of accessibility constraints when travelling for caring trips (for example, when accompanying someone with limited physical mobility), less choice over times of travel, and a smaller total time budget for travel.

- **Consequences:** Greater stress associated with delays and disruption to caring trips, and greater likelihood of knock-on consequences where time budgets are highly constrained due to caring responsibilities.
- **Needs:** A greater number of trips overall, and a greater need to travel between neighbourhoods, and the greater potential for unexpected or unplanned trips.
- **Extent of impact:** Having caring responsibilities does not always increase the risk of TRSE, but is likely to do so where the time required is significant, and where responsibilities generate large numbers of additional trips. This effect is also more likely where caring responsibilities are combined with a low household income.

4. Disability and poor health

- **Constraints:** Greater accessibility constraints when travelling, greater exposure to harassment and discrimination, greater reliance on support when travelling, and the potential for greater transport costs (for example, adapted vehicles).
- **Consequences:** Greater likelihood of unemployment if transport issues impact access to work, greater administrative effort required to travel which can increase in response to transport issues (for example, having to rebook staff support), and greater barriers to accessing services meaning greater consequences from delays and service cancellations.
- **Needs:** A greater need to travel to access healthcare and other support services, which may be linked to a disability or health condition.
- **Extent of impact:** The extent of this effect depends on the nature of disability or health condition. It is also closely tied with the impacts of disability on income. Those with a disability or health condition that has a major impact on their everyday life, and who are also on a low income, are most likely to be impacted.

5. Other population characteristics

Alongside the key population characteristics linked to TRSE above, our research also shows that women, some ethnic and religious minority communities, younger and older people, and LGBTQ+ people are more likely to face TRSE than those outside of these groups. In general, this reflects the greater exposure of these populations to harassment, discrimination or anti-social behaviour when travelling by public transport and active travel, and the greater impacts of safety concerns on the transport choices of these populations.

While potentially significant, these impacts are deeply contextual. Consequently, it would not be reasonable to assume higher levels of TRSE vulnerability based on the level of these population groups within a small area (for example, a higher vulnerability because of a higher percentage of residents of an area being women). Consequently, these population characteristics cannot be treated in the same way as other elements of TRSE vulnerability, where the relationship is more direct. Rather, our approach focuses on the key underlying elements that cause these variations – for example, the gendered distribution of incomes and caring responsibilities.

Vulnerability index development process

Our approach to estimating vulnerability to social exclusion is to translate the set of population characteristics in the previous section into a quantitative index. This index is intended to capture the nuances of these characteristics, the correlations between these characteristics, and their relative importance in determining TRSE. Reflecting this, we undertook the following process:

1. **Long listing:** We developed a long list of indicators of vulnerability to TRSE, linked to the outcomes of TfN's primary research with residents across the North, the experience of developing V2, and by considering the set of indictors used to develop the 2019 IMD.

2. **Geographical conversion:** Where required, we converted datasets structured in 2011 OAs into 2021 OAs, using a distance-based weighting structure to avoid distortions caused by population growth and movements.

3. **Factor analysis:** We undertook factor analysis of ranked indicators to identify statistically robust groupings within the dataset. This involved an exploratory and iterative process of adjusting indicators, comparing unrotated and rotated results, and adjusting the number of factors extracted. This produced three factors.

4. **Index generation:** We produced a composite vulnerability index, using factor analysis to weight and group indicators. This included comparing the distribution and contribution of the three factors extracted in the factor analysis process in determining an area's position in the combined index.

Long listing

Our approach to long-listing indicators was shaped by the following principles:

1. Metrics derived from indicators must be shareable using an Open Government Licence. This is necessary in order to provide a transparent and public-facing tool, consistent with V2.
2. Indicators must be relatively recent and applicable to 2024, with the 2021 Census selected as a cut-off point for the age of data.
3. All indicators must provide England-wide coverage, with consistent quality across England, and adhere to a consistent spatial structure.
4. All indicators must be available at the 2021 Census output area level, or at the middle-layer super output area level where these are used to identify broader area-based characteristics.
5. Elements of the 2021 Census that are likely to have been significantly distorted by COVID-19 should only be used in a way that reflects the likely degree of uncertainty that is present because of this (particularly labour market data).
6. Each of the characteristics linked to TRSE should be measured by several indicators, so that these themes are not entirely reliant on single sources.

Based on this process, we developed the following long list of indicators, which were taken forward into the factor analysis. These indicators are grouped by theme.

1. Low household income

Indicator	Source	Period
Number of recipients of working age low-income benefits	DWP Stat-Xplore	Most recent 12 quarters
Number of recipients of retirement age low-income benefits	DWP Stat-Xplore	Most recent 12 quarters
Number of children in relative low-income households	DWP Stat-Xplore	Most recent 12 quarters
Number of residents who are out of work and have never worked	2021 Census	March 2021
Number of residents that have not worked in the last 12 months	2021 Census	March 2021
Number of residents who could not work from home	2021 Census	March 2021
Number of households that are socially rented	2021 Census	March 2021
Number of households that are not owned outright	2021 Census	March 2021
Area net income after housing costs	ONS	2022

2. Insecure work

Indicator	Source	Period
The set of indicators of low household income, with the addition of:		
Number of residents with no degree-level qualifications	2021 Census	March 2021
Number of residents with no formal education qualifications	2021 Census	March 2021
Number of residents aged 16 to 24	2021 Census	March 2021

3. Caring responsibilities

Indicator	Source	Period
Number of recipients of carer's allowance	DWP Stat-Xplore	Most recent 12 quarters
Number of residents that provide unpaid care	2021 Census	March 2021
Number of residents providing more than 20 hours of care per week	2021 Census	March 2021
Households containing one adult and one or more dependent children	2021 Census	March 2021
Households containing dependent children	2021 Census	March 2021
Number of children in relative low-income households	DWP Stat-Xplore	Most recent 12 quarters
Number of residents aged 0 to 15	2021 Census	March 2021
Number of residents aged 85 and above	2021 Census	March 2021

4. Disability and poor health

Indicator	Source	Period
Number of recipients of disability-related benefits	DWP Stat-Xplore	Most recent 12 quarters
Number of residents that identify as disabled	2021 Census	March 2021
Number of residents that say that their disability impacts day to day life a lot.	2021 Census	March 2021
Number of residents that described their health as bad or very bad	2021 Census	March 2021

5. Other characteristics

Indicator	Source	Period
Number of residents that cannot work from home	2021 Census	March 2021
Number of households without access to a car or van	2021 Census	March 2021
Number of residents that cannot speak English well or at all	2021 Census	March 2021
Levels of violent crime and theft	Data.Police.Uk	Most recent 12 months

Geographical conversion

Indicators derived from DWP Stat-Xplore are significant to several of the themes of this analysis, and are more regularly updated than data derived from the 2021 Census. However, these data are currently structured in 2011 OAs, rather than the 2021 OAs from the 2021 Census.

The ONS provide lookup tables for a 'best fit' translation of 2011 OAs to 2021 OAs. However, due to the increase in the total number of OAs and changes to the distribution of populations within OAs between 2011 and 2021, this type of one-to-one translation would not provide acceptable OA-level metrics for this analysis. In particular, using this approach would mean that metrics for some new population centres (for example, a new housing estate built in an otherwise rural area) would be solely-reliant on a single nearest OA, even if this was a considerable distance away from the new population centre. Examples of this are provided overleaf.

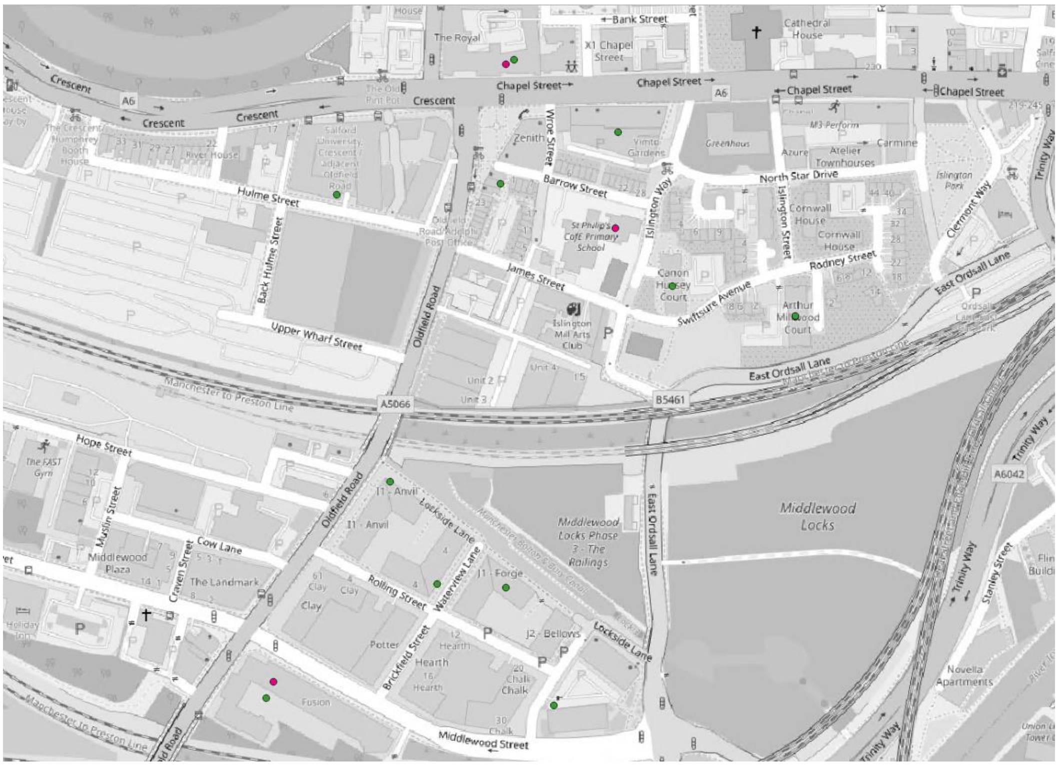
Reflecting the limitations of the 'best fit' translation available from the ONS, we instead engaged a distance-weighted matching process between 2011 and 2021 OAs. To do so, we first matched each 2021 OA population-weighted centroid (PWC) to the nearest 2011 OA PWC, measured in a straight line. We then applied the following matching process:

2011 to 2021 OA PWC distance	Matching process
Less than 100 meters	Nearest only
100-200 meters	Matched to nearest 2, capped at 200 meters
200-500 meters	Matched to nearest 4, capped at 500 meters
Greater than 500 meters	Matched to nearest 6, capped at 5000 meters

Through this matching process, we assigned each 2021 OA PWC one or more 2011 OA PWCs, with a measure of distance. 96% of 2021 OAs are matched to a single 2011 OA, 1.6% to two 2011 OAs, and 1.9% to three or more 2011 OAs. Where a 2021 OA was matched with more than one 2011 OA, we implemented distance-based weighting. Under this approach, each 2011 OA is weighted based on the distance between each of the set of 2011 OA PWCs and the 2021 OA PWC.

The distance-based weighting applied when aggregating from 2011 to 2021 OAs is linear and relative. This means that, for a given 2021 OA with two matched 2011 OAs, if the second closest 2011 OA PWC is double the distance from the closest 2011 OA PWC, it has half the weight of the first. As the final step in this process, metrics for each 2021 OA are constructed using the distance-weighted total of the set of matched 2011 OAs.

Example of urban population growth creating the potential for over-dependence on single 2011 OAs (2011 OA PWC in pink, 2021 OA PWC in green)



Example of rural population growth creating the potential for significant spatial mismatch (2011 OA PWC in pink, 2021 OA PWC in green)

Factor analysis

Taking the five groups in the long listing process as a starting point, we undertook exploratory factor analysis to examine the statistical structure of variables within and between these groups, and to support in producing a composite vulnerability index.

Our factor analysis uses ranked data, standardised to the size of the population. For most variables, ranks were constructed based on proportion of the total of each OA that has a given characteristic. The exception to this is the following two area-based variables: (1) Average household income after housing costs, and (2) levels of crime. These do not require standardisation by the size of the population, and were instead ranked directly.

Our use of ranked standardised data for the factor analysis was driven by two considerations: First, many variables included in the long list exhibit a high level of skewness and kurtosis. Second, a small number of variables contain a significant number of outliers, in excess of 5 standard deviations from the mean. In both cases this is particularly evident for the level of crime, the proportion of the population that cannot speak English, and the proportion of the population that is aged 16 to 24.

Variable	Skewness	Kurtosis
Level of crime	3.2	15.6
Population that cannot speak English well or at all	4.3	37.0
Population that is aged 16 to 24	6.1	53.0

While it would have been possible to reduce the scale of these issues through a combination of removing outliers above a given threshold and statistical transformations, we instead elected for ranking. Our reasons for this are twofold:

First, this approach avoids having to remove outlier values, and therefore leaving some OAs with missing values for one or more variables. Since these datasets were not developed by TfN, our capacity to determine if outlier values are faulty or genuine is limited, and our decisions would therefore have to follow arbitrary statistical thresholds. For a small proportion of OAs (<1%), this would mean 3 variables having missing values, significantly impacting overall outcomes.

Second, ranking data is consistent with our aim to construct a relative index of vulnerability, based on multiple variables. Compared with statistically transformed proportions, these ranks are more intuitive to interpret, and are of consistent scale, range, and distribution.

Based on an Eigenvalue threshold of 1, we initially extracted four factors. This resulted in cross-loading on 16 variables, including 10 negative cross-loadings. Applying rotation, and trialling multiple rotation methods marginally improved this, with 9 variables cross-loading under Direct Oblimin rotation. Adding a fifth factor was trialled with and without rotation, but this did not significantly reduce the extent of crossing loading, and typically resulted in only one variable loading on the fifth factor. Because of this, we incrementally removed the following variables, at each stage considering the factor loadings with and without Direct Oblimin rotation:

- Number of residents that have not worked in the last 12 months
- Number of residents that provide unpaid care
- Number of residents that say their disability impacts day to day life a lot
- Area net income after housing costs
- Levels of violent crime and theft
- Number of residents aged 85 years or over

Our decision to remove these variables was based on the outcomes of incrementally repeating the factor analysis process, and on our underlying reasons for selecting these variables in the long-listing process. In all cases apart from the level of crime, these measures were overlapping to others in the dataset. For example, for the proportion of residents ages 85 years and over, we were intending to capture the impacts of poor health, disability, and social isolation.

The final outcome of our factor analysis, based on this reduced set of variables, was a three-factor solution, obtained using Direct Oblimin rotation. The tables below show the variables which load on to each factor, and the corresponding loading.

1. Factor One: Disability, caring, and poor health

Variable	Loading
Recipients of carer's allowance	0.69
Recipients of disability-related benefits	0.71
Residents with no formal education qualifications	0.81
Residents with no degree-level qualifications	0.84
Residents who could not work from home	0.81
Residents that provide more than 20 hours of unpaid care per week	0.84
Residents that identify as disabled	0.85
Residents that described their health as bad or very bad	0.80

2. Factor Two: Childcare and young people

Variable	Loading
Households containing one adult and one or more dependent children	0.60
Households containing dependent children	0.94
Children in relative low-income households	0.50
Residents aged 0 to 15	0.92

3. Factor Three: Poverty and insecure work

Variable	Loading
Recipients of working age low-income benefits	0.73
Recipients of retirement age low-income benefits	0.60
Residents who have never worked	0.54
Households that are not owned outright	0.87
Households that are socially rented	0.66
Households without access to a car or van	0.89
Residents that cannot speak English well or at all	0.73
Residents aged 16 to 24	0.49

The three factors obtained through the factor analysis process differ significantly from the original groupings in the long-listing process. This reflects the extent of inter-connectedness between measures of poverty and insecure work, and between disability, ill health, and caring responsibilities. While the Direct Oblimin rotation used to develop this factor structure allows for a limited degree of correlation, this structure provides largely independent measures of aspects of TRSE vulnerability. The table below shows the correlation matrix between the three factors.

Factor	1	2	3
1	1	0.22	0.48
2	0.22	1	0.45
3	0.48	0.45	1

Index generation

To develop the index of vulnerability, we combined ranked data for each OA using a weighting derived from the factor loading. This weight is equal to the variable loading divided by the total loading for all variables on that factor. The combined index is the sum of the factors, equally weighted. Our decision not to apply additional weighting in creating the final index is based on the following considerations:

1. This approach avoids translating evidence-based but relatively subjective judgements about the balance of different factors into quantitative metrics. Instead, each element of TRSE vulnerability we have defined through the factor analysis process has equal influence on the combined index.

2. It reflects the degree of uncertainty inherent in assessing disabilities and caring responsibilities using the dataset available – particularly the data obtained from the 2021 Census. More precise data may have enabled different decisions about the relative balance of the three factors.

3. The specification of each factor includes some variables linked to poverty. This is important as, in general, our research demonstrates that poverty is fundamental to TRSE, and that it exacerbates vulnerability linked to disability and caring responsibilities.

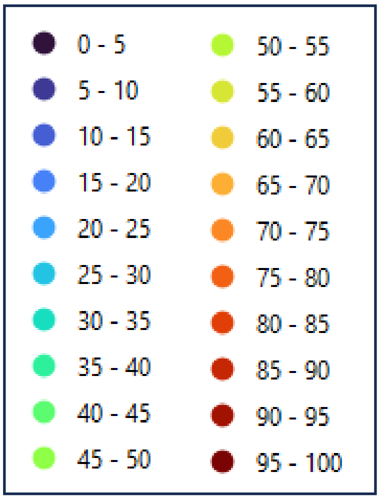
The vulnerability index we produced through this process provides each OA with an overall rank, based on the combined total of the three factors, and a rank on each factor. The table below compares the distribution of OAs in the 1st, 5th, and 10th deciles on the overall vulnerability index. For each decile in the overall index, the table shows the percentile distribution of OAs. For example, the 1st decile in the overall index contains OAs that are in the 1st and 63rd percentile on factor one, with most OAs being between the 7th and 27th percentile on this factor.

	1st decile			5th decile			10th decile		
Factor	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**	**F1**	**F2**	**F3**
Minimum	1	1	1	1	1	7	47	48	59
Maximum	63	62	64	100	99	100	100	100	100
Range	63	62	64	100	99	93	53	52	41
Quartile 1	7	8	3	31	32	40	80	84	83
Quartile 2	15	17	7	49	52	49	89	92	89
Quartile 3	27	28	15	67	70	62	95	96	95
Inter-quartile range	20	20	12	36	38	22	15	12	12

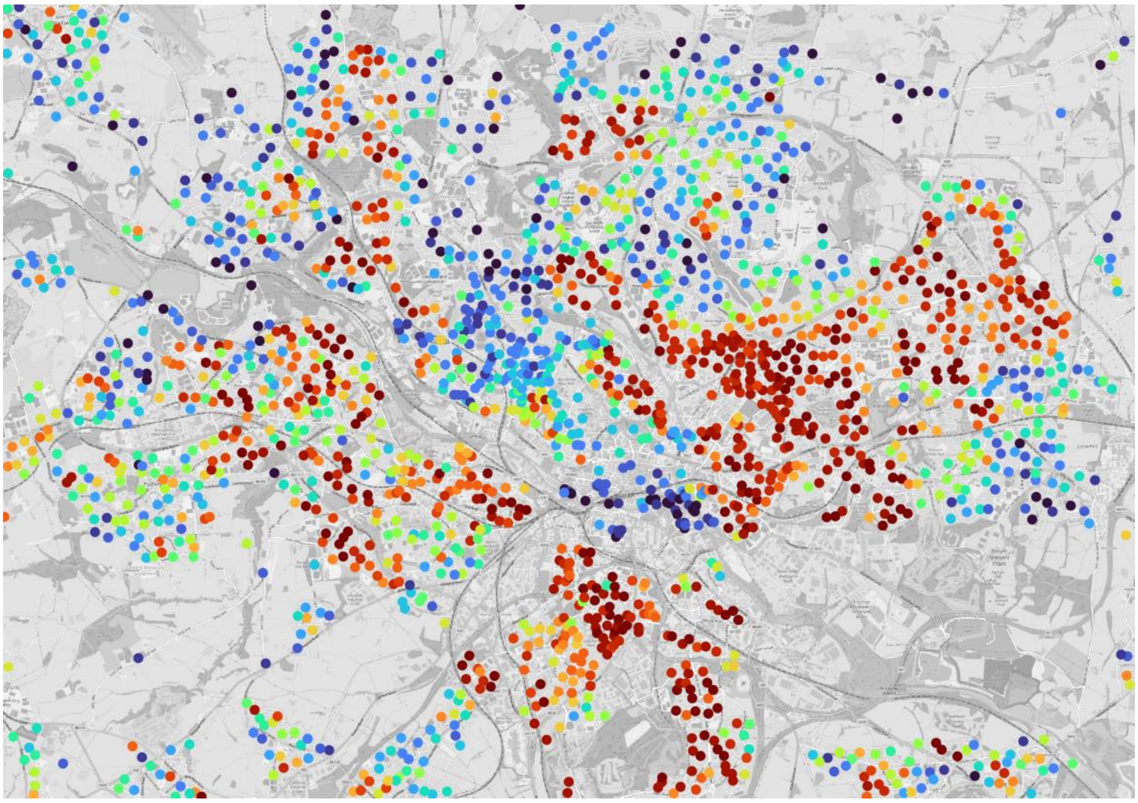
The table demonstrates significant diversity between OAs in the same overall decile. This is most pronounced in the middle of the overall distribution – with the 5th decile overall containing OAs in the 1st and 100th percentile on factor one and the 1st and 99th percentile on factor two – but is also present for OAs in the 1st and 10th decile overall. As we intended in the development of this index, this demonstrates the potential for combinations of vulnerability across income, disability, caring responsibilities, and other elements to produce high, medium, and low levels of overall vulnerability. This recognises and reflects the diverse sets of circumstances that exacerbate the impacts of transport issues on everyday life, and result in social exclusion.

The maps overleaf show the variation in the overall level of vulnerability to social exclusion, and in each of the three factors underlying this, in Leeds. In this example, one of the largest contrasts evident is in the concentration of poverty and insecure work and the other two underlying factors in the central and western communities of the area covered. These maps also demonstrate the hyper-local variation in the overall index and the three underlying factors. In each case, OAs are displayed by their percentile, where 0 is the lowest level of vulnerability to social exclusion, and 100 is the highest level.

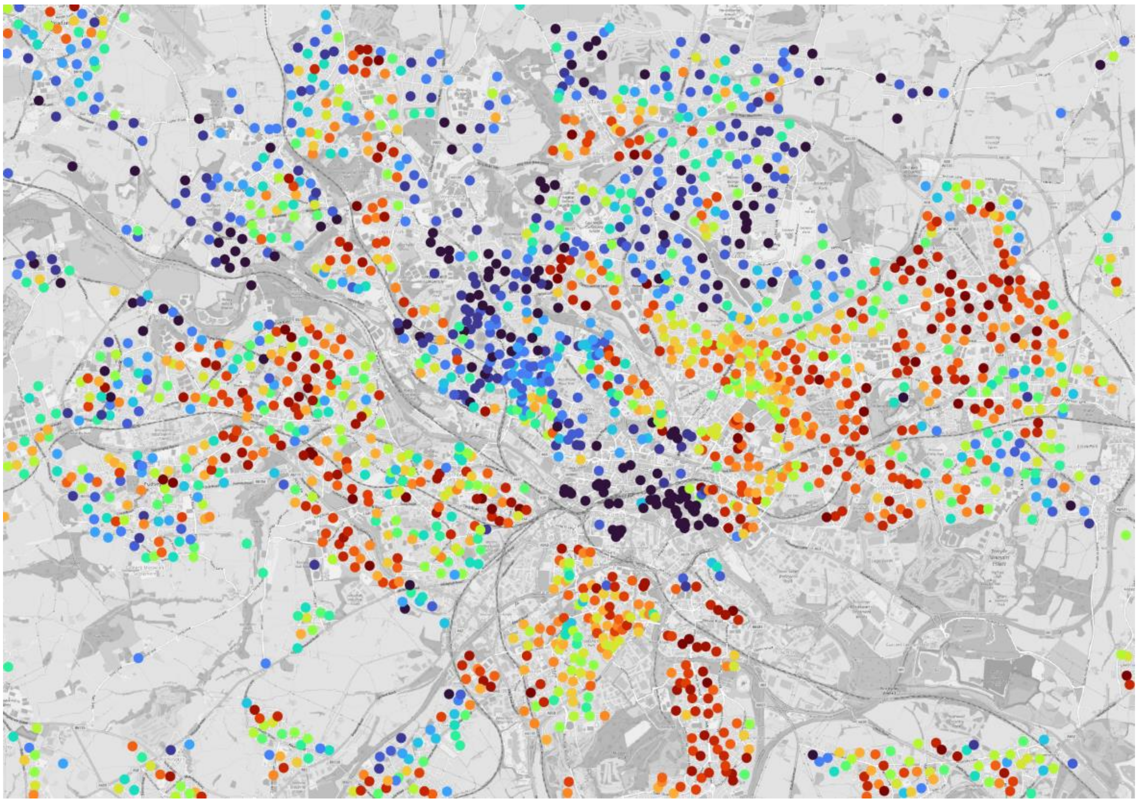
Map legend: Percentiles



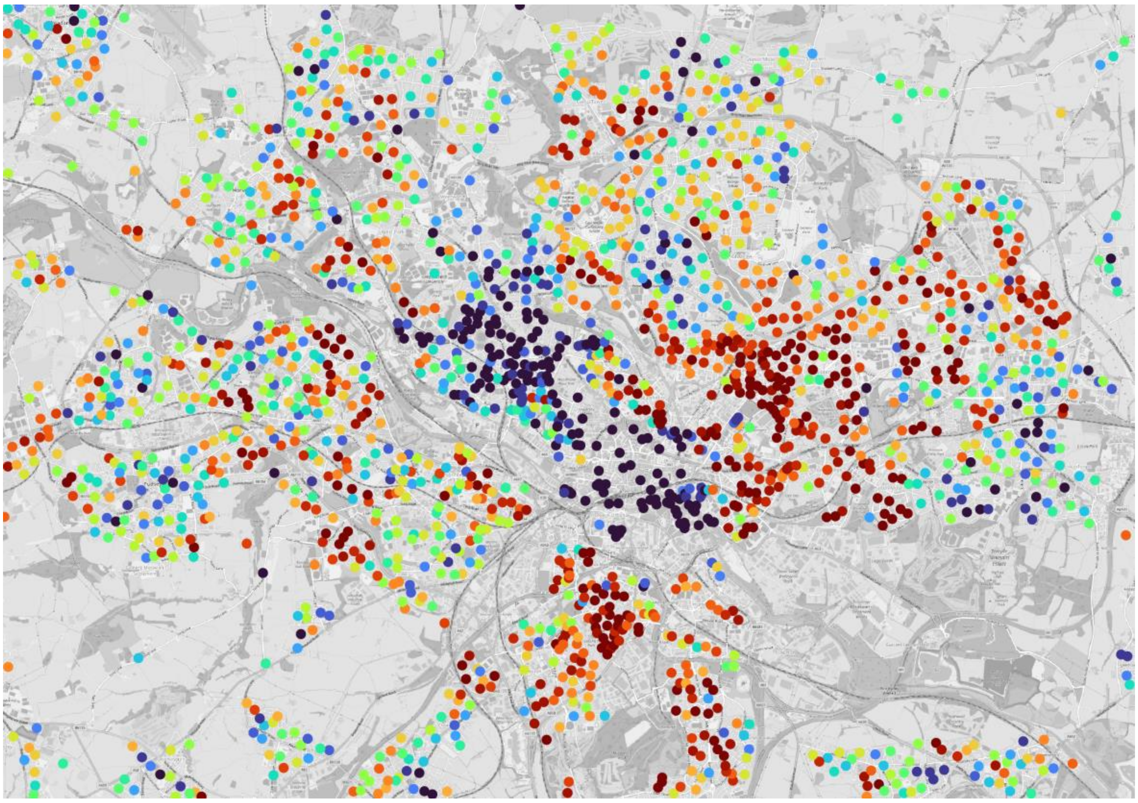
Overall vulnerability to social exclusion



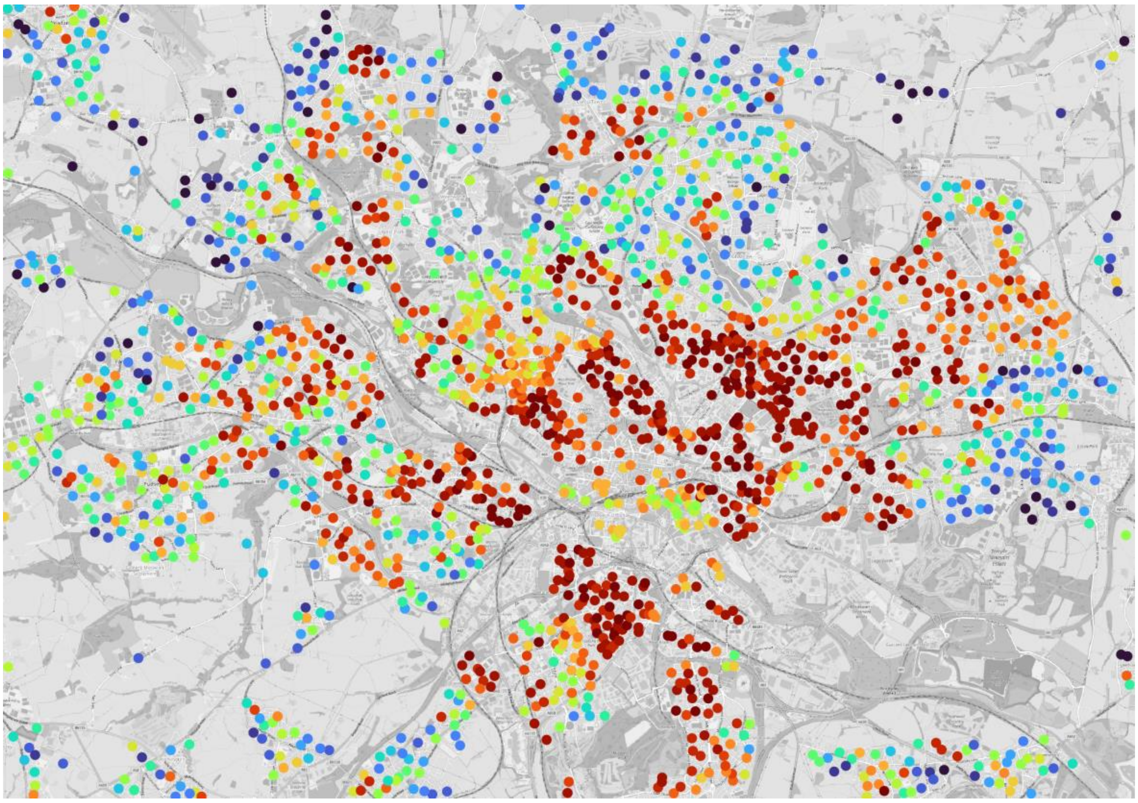
Factor One: Disability, caring, and poor health



Factor Two: Childcare and young people



Factor Three: Poverty and insecure work



TRANSPORT FOR THE NORTH

Appendix 2: Measuring access to everyday destinations in local areas of England

Background

TfN's TRSE tool combines an access analysis and a vulnerability analysis to estimate the risk of social exclusion caused by a range of issues with public, private, and active transport systems. The access analysis we used in TRSE tool V2 engaged outputs from DfT's 2019 Journey Time Statistics datasets. We adopted this measure because, at the time that V2 was developed, it provided a relatively recent means of assessing access to a range of destinations across England, which could be readily converted into metrics for the TRSE tool. However, for TRSE tool V3 we have developed a new and bespoke access index.

The following factors have influenced our decision to develop this new index for V3:

6. The DfT Journey Time Statistics (JTS) datasets have not been updated since 2019, and at the time of writing the schedule for updates to these datasets is not known. DfT have developed a connectivity assessment tool, which is intended in part to replace the JTS datasets, however the nature of local level data provided is currently unknown. Consequently, there is a high degree of uncertainty over the future of these datasets.

7. Previous releases of the DfT JTS have grouped data by Census lower-layer super output areas (LSOAs). While generally sufficient for urban areas, this has significant limitations in sparsely populated rural areas, where LSOAs cover relatively large geographical areas. Users of the TRSE tool focusing on rural areas have requested a greater level of spatial detail than LSOA.

8. The DfT JTS provided coverage for many but not all of the destinations that our research identifies as key to TRSE among residents of the North. For example, access to pharmacies, banks, and supermarkets is not currently possible with the DfT JTS, and there are limitations in the coverage of access to work. Developing a bespoke set of access metrics allow us to determine the range of destinations examined, in line with the outcomes of our research.

9. The DfT JTS is based on a single time period – a weekday morning peak. This is a period in which the coverage and frequency of public transport networks is relatively high, and in which the level of road traffic congestion is also relatively high. Consequently, using this time period alone is likely to supress the true extent of access inequality between modes. Alongside this, this period is much more relevant for employment and education journeys than for other equally key journey types, such as those for caring responsibilities.

Based on these factors, we have developed a new TRSE access index for V3, which we combine with new vulnerability data to estimate TRSE risk across England. Through this, we have produced a metric with a more predictable update schedule and a finer level of spatial detail, and which is shaped by our research on TRSE.

Defining access to everyday destinations

Our objective is to produce a relative index of access to the range of destinations that residents of the North and elsewhere in England require as part of everyday life. In doing so, we are seeking to reflect as much of the reality of everyday travel as possible, within constraints created by the geographical scale of our analysis, the level of spatial detail required, the datasets available, and the diversity inherent in different lifestyles, life stages, and preferences. Where possible, we are also seeking to maintain broad comparability with the access analysis used in V2.

Our research shows that there is a broad set of destination types that are relevant to TRSE. Reflecting our focus on social exclusion, our intention here is not to attempt to cover all destination types that a resident could conceivably want to access in a typical week. Rather, our intention is to measure access to destinations which are significant to the full and meaningful social participation of residents – the absence of which will contribute to social exclusion. Our research indicates that this includes the following, which we refer to as 'key everyday destinations' throughout:

- **Work**
  - Current workplace
  - Job opportunities

- **Education**
  - Primary schools
  - Secondary schools
  - Further education

- **Healthcare**
  - Hospitals
  - GP surgeries
  - Outpatient facilities not connected to a hospital or GP
  - Dentists
  - Pharmacies
  - Care and support services

- **Basic shops, services, and amenities**
  - Supermarket
  - Town or retail centre
  - Bank or building society
  - Park or other green space

- **Family, community, and social life**
  - Homes of friends and family members
  - Childcare
  - Social care and support services for adults and children

    - Religious and community centres

Our research and the wider TRSE research literature demonstrates that there are a range of factors that shape access to these key everyday destinations. This includes:

- Journey times
- Journey costs
- Journey reliability, including integration between modes
- Perceptions of safety
- Accessibility for those with disabilities and limited mobility
- Perceptions of ease, desirability, and comfort
- Information, habits, and behavioural norms

These determinants of access form a complex picture, which will vary across different individuals, as well as between different journey purposes, how often a journey is taken, and the time of day - among other factors. The role of habit and behavioural norms within this should not be underestimated, particularly when considering how travel behaviours respond to new public transport routes or improvements to active travel conditions.

The complex set of determinants of access creates a challenging environment for developing a generalised metric of TRSE across England, particularly at the neighbourhood level. Journey times are directly measurable with the data and modelling tools available, however none of the other factors listed above can be directly and consistently measured. Consequently, our access analysis focuses on journey times, and our vulnerability analysis is used as a proxy for the impacts of some of the other factors. For example, we measure income deprivation and poverty to reflect the impact journey costs, and we measure disability and health conditions to reflect the impacts of poor accessibility.

As an area-based measure of TRSE, our analysis is unable to consider influences on access that are purely or predominantly perceptual. Of the above, this particularly applies to perceptions of safety, of ease, desirability, and comfort, and of information, habits, and behavioural norms. These are factors which vary predominantly at the household and individual level, rather than between small geographical areas. Consequently, the tool is not a replacement for direct engagement with communities, particularly on these wider determinants of access to key everyday destinations.

Access index development process

Our approach to measuring access to key everyday destinations is as follows:

5. **Destination long listing:** We developed a long list of key everyday destinations, based on the outcomes of research with communities in the North. We arranged this in five categories – work, education, healthcare, basic services and amenities, and family, community, and social life.

6. **Data searches:** We identified non-commercial datasets that provide the location of destinations in the long list, and could do so consistently on a national basis. While our analysis focuses on England, this includes border areas of Scotland and Wales, where it is possible that a cross-border destination will be the most accessible option. No suitable datasets were found for: Outpatient facilities not connected to a hospital or GP, Care and support services, Homes of friends and family members, Childcare, social care and support services for adults and children, and religious and community centres. Consequently, the family, community, and social life group was dropped.

7. **Data filtering:** We filtered the destination datasets to ensure they were relevant for our analysis of key everyday destinations. For example, we imposed a minimum size requirement on public parks and town / retail centres, we removed fee-paying schools, and non-NHS hospitals. We also removed closed, planned, and temporary facilities.

8. **Data conversion and cleaning:** We removed duplicate data, and checked for quality and consistency across the relevant geography. We did so by comparing data snapshots to other sources, such as Open Street Map and Google Maps. Where required, we also converted polygon datasets to point data, and used postcode point data to identify locations where coordinates were not provided.

9. **Time period matching:** We identified three time periods for our access analysis – a weekday morning peak time, a weekday evening post-peak time, and a weekend afternoon. We selected these three time periods as a balance between the need to expose differences between times of day, and to retain relevance to the pattern of real world journeys.

10. **Computation feasibility and adjustment:** We assessed the feasibility of conducting an access analysis with each resulting destination dataset with the resources available. As a result of this, we first reduced the number of points in the 'park or other green space' and 'town or retail centre' datasets. We did this by reducing the density of boundary line points from 400 meters to 600 meters, with a minimum of two points per polygon. However, the green spaces dataset still exceeded the feasible maximum with the computational resources available, and consequently was removed.

11. **Access modelling:** We used Basemap TRACC to determine journey times from all population-weighted output area centroids in England to the destinations included. We did so for car travel, and for all-mode public transport. For the majority of destinations, we measured journey time to the closest two destinations for each mode and in each time period. Additionally, for employment, we examined the total number of jobs accessible within 60 minutes, assessed using LSOA-linked job count data.

12. **Metric development:** Using outputs from our access modelling, for each output area we examined the overall level of access to each destination by each mode and in each time period, using a defined time threshold for each destination. We also examined journey time for each, inequality in journey time between modes, and inequality in journey time between time periods. This provides a range of relative and absolute measures of access to key everyday destinations with the transport options available in an area.

13. **Index development:** As the final step of the analysis, we ranked each OA on each measure, and used this to produce a rank of average ranks for each destination group (work, education, healthcare, and basic services and amenities). Our overall access index is the rank of average ranks across these four groups.

Destination long listing

Based on the outcomes of our primary research with communities across the North of England, we identified the following destinations as key to TRSE:

- **Work**
  - Current workplace
  - Job opportunities

- **Education**
  - Primary schools
  - Secondary schools
  - Further education

- **Healthcare**
  - Hospitals
  - GP surgeries
  - Outpatient facilities not connected to a hospital or GP
  - Dentists
  - Pharmacies
  - Care and support services

- **Basic shops, services, and amenities**
  - Supermarket
  - Town or retail centre
  - Bank or building society
  - Park or other green space

- **Family, community, and social life**
  - Homes of friends and family members
  - Childcare
  - Social care and support services for adults and children
  - Religious and community centres

Data searches

After the long listing process, we conducted searches for datasets as follows:

Category and type	Available	Source and notes
Work		
Current workplace	No	No data exists that would allow us to identify specific employment locations access from specific OAs.
Job opportunities	Partially	Data on employees from the ONS Business Register and Employment Survey, used as a proxy for job opportunities. Data link.
Education		
Primary schools	Yes	ONS / Gov.UK. Data link
Secondary schools	Yes	ONS / Gov.UK. Data link
Further education	Yes	ONS / Gov.UK. Data link
Healthcare		
Hospitals	Yes	NHS England. Data link.
GP surgeries	Yes	NHS England. Data link.
Outpatient facilities	Partially	NHS England provide information, but there are limitations in classification that would impact the analysis. Data link.
Dentists	Yes	Care Quality Commission. Data link.
Pharmacies	Yes	General Pharmaceutical Council. Data link.
Care and support services	Partially	Data could be compiled from the Care Quality Commission, but there are limitations in classification that would impact the analysis. Data link.

Basic shops, services, and amenities		
Supermarkets	Yes	Geolytix. Data link.
Town and retail centres	Yes	CDRC Retail Centre Boundaries and Open Indictors. Data link.
Banks	Yes	Geolytix. Data link.
Parks and green space	Yes	Ordnance Survey. Data link.
Family, community, and social life		
Homes of friends and family	No	No data exists that would allow us to identify specific neighbourhoods or areas relevant to specific OAs.
Childcare	Partially	Data could be compiled from Ofsted, however there are exclusions and limitations. Data link.
Social care and support services	Partially	Data could be compiled from the Care Quality Commission, however there are exclusions and limitations. Data link.
Religious and community centres	Partially	Data is available for religious buildings, but not for community centres.

At this stage, the following destinations were dropped from the analysis, due to limitations in the data which would preclude a sufficiently accurate access analysis:

- **Work:** Current workplace.
- **Education:** None.
- **Healthcare:** Outpatient facilities, care and support services.
- **Basic shops, services, and amenities**: None.
- **Family, community, and social life:** Homes of friends and family, childcare, social care and support services, religious and community centres.

Data filtering

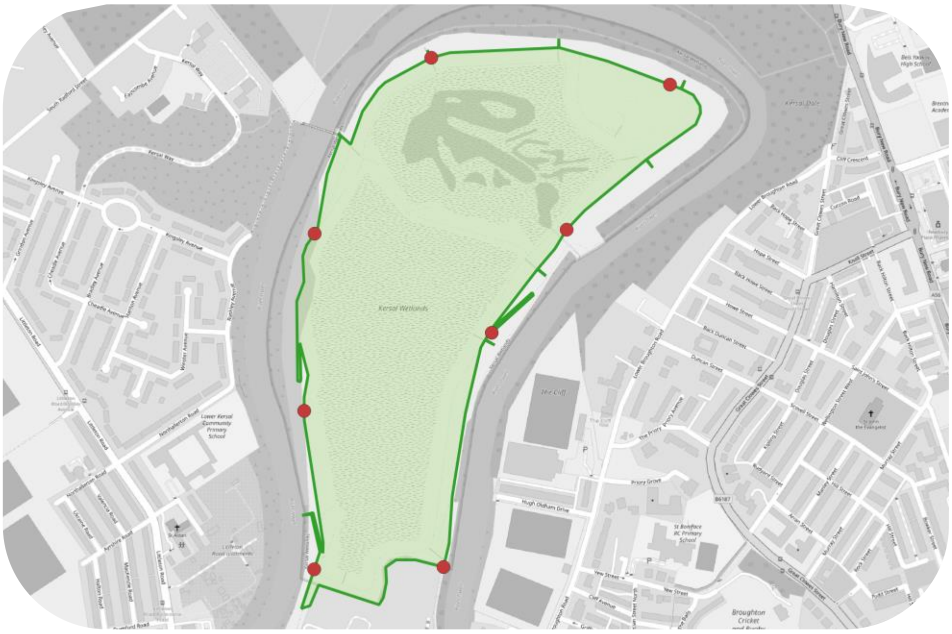
We then applied the following filtering to the remaining datasets:

Work	
Job opportunities	We identified a major employers dataset by filtering LSOAs with more than 5,000 employees, and Scottish Data Zones with more than 3,500 employees. The all-employers dataset includes all those with more than 50 employees.
Education	
Primary schools	We filtered by relevant age and type categories, and then removed closed and proposed schools, online-only providers, and boarding schools.
Secondary schools	We filtered by relevant age and type categories, and then removed closed and proposed schools, online-only providers, and boarding schools.
Further education	We filtered by relevant age and type categories, and then removed closed and proposed colleges, and online-only providers.
Healthcare	
Hospitals	We filtered by size, type, and specialism, to identify major general hospitals. This process was closely comparable to the 2019 DfT JTS process.
GP surgeries	We selected those where the number of registered patients was greater than zero.
Dentists	We selected those where the number of registered patients was greater than zero.
Pharmacies	We removed pharmacies in hospitals, in prisons, and those that are online-only.
Basic shops, services, and amenities	
Supermarkets	We removed supermarkets smaller than 280m2, based on the size category where Sunday trading laws apply.
Town and retail centres	We removed those categorised as ‘small local centres’.
Banks	We removed those categories as ‘closed’ and ‘closing’, and filtered all but ‘branch’ and ‘agency’ types.
Parks and green space	We selected those categorised as ‘public park or garden’, and filtered based on a 10,000 square meter size threshold.

Data conversion and cleaning

At this stage, as well as removing duplicates that would impact the count of destinations reached, we compared 10 data snapshots to Open Street Map and Google Maps. Within each snapshot, we identified if the destinations identified matched these other sources, if the location was as expected, if there were any missing data points, and if there were any additional or unexpected data points. Each snapshot was a 100m x 100m grid, chosen randomly from a grid set across the land area of England. This process provided an additional check on the quality and coverage of the destination datasets.

Alongside cleaning and cross-checking the data, we also converted polygon datasets to point data, and used postcode point data to identify locations where coordinates were not provided. Two data destination datasets required conversion from polygon to points: Town and retail centres, and parks and green spaces. Points were initially added at 400-meter intervals along the outer perimeter of each polygon, excluding any internal gaps, and with a minimum of two points per polygon. This is shown in the example below.



Adding points to the boundaries of polygon is a practical but imperfect solution to two problems: First, a lack of consistency in the data available on entry and exit points to green spaces and retail centres. Second, the very large number of entry and exit points in the datasets available, which poses major computational challenges for an access analysis. The Ordnance Survey green spaces dataset used, for example, contains approximately 297,000 access points. The approach described here reduced this to approximately 43,000. These points do not correspond with actual access and entry points, but do form a reasonably accurate and more practical proxy.

Time period matching

Following data conversion and cleaning, we matched each destination to a time period. Our intention in doing this was to identify the most relevant times in which those accessing each destination type would depart. To inform this process, we used the extensive primary evidence base we have gathered from residents of the North of England, and supplemented this with data from the National Travel Survey. We sought throughout this process to be evidence-led, however finalising this list entailed subjectivity and professional judgement.

Destination	Weekday AM peak	Weekday PM post-peak	Weekend PM
Large Employers	X	X	X
All employers	X	X	X
Primary Schools	X		
Secondary school	X		
FE college	X	X	X
Major hospital	X	X	X
GP surgery	X	X	X
Dentist	X	X	
Pharmacy	X	X	
Large supermarket	X	X	X
Town or retail centre	X	X	X
Bank	X		X
Parks & green space	X	X	X
Total	**13**	**10**	**9**

Computation feasibility and adjustment

At this stage, we assessed the feasibility of conducting an access analysis at the Output Area level for each of the destination datasets, using Basemap TRACC. The main constraint was the total number of origin-destination pairs, which has a stable maximum of 1.5 billion per run. The table below shows the number of origin points

Destination	Points	Pairs (billions)	Runs per period	Time periods	Runs for 2 modes
Large Employers	1,000	0.18	1	3	6
All employers	34,000	6.05	5	3	30
Primary Schools	16,837	2.99	2	1	4
Secondary school	3,805	0.68	1	1	2
FE college	347	0.06	1	3	8
Major hospital	239	0.04	1	3	8
GP surgery	6,594	1.17	1	3	8
Dentist	9,355	1.67	2	2	8
Pharmacy	10,552	1.88	2	2	8
Large supermarket	7,230	1.29	1	3	8
Town or retail centre	7,990	1.42	1	3	8
Bank	4,274	0.76	1	2	6
Parks & green space	42,832	7.97	6	3	36
Total	**145,055**	**26.16**	**25**	**32**	**140**

The total computational demand for all destinations, time periods, and modes exceeded the resources available, which was approximately 100 runs.

The time periods defined in the table above were already set at a minimum for what we deemed a reasonable access analysis. Reflecting this, our first approach was to attempt to reduce the number of destination points in the town or retail centre and parks and green space datasets, which had been converted from polygons. However, we judged that reducing beyond the 400-meter point density previously selected to the extent required would undermine the accuracy of the analysis, particularly in smaller green spaces and retail centres. Consequently, we retained the full town and retail centre dataset, and removed the parks and green space dataset from the analysis at this stage.

Access modelling

For each destination, time period, and mode combination, we used Basemap TRACC to determine a journey time. For all but the “all employers” destination, we did this for the closest two destinations, so as to enable analysis of choice as well as pure access. For All Employers, we assessed the full reach within a 1-hour travel time.

For access by car, we used the OS MasterMap Highway Network and the OS Highway Routing and Asset Management (RAMI) database. This includes average speed data at different times of day, enabling us to factor the impacts of congestion into the analysis. We applied a maximum distance between origin and destination of 100 kilometers, on a normalised network. A normalised network was used due to the significant improvements in computation performance this brings, with only marginal impacts on journey time results,

For access by public transport, we used the OS MasterMap Highway Network to provide the base network for walking access to public transport access points, and scheduling and interchange data provided through Basemap Datacutter. Our public transport analysis is multi-modal, including travel by bus, coach, ferry, light and national rail, metro, and tram where these are available. It also includes interchanges between modes and services, subject to a minimum 5-minute interchange time. We applied an average walking speed on the network of 4.8 kilometers per hour, and 4 kilometers per hour off of the network. As with access by car, we also applied a maximum distance of 100 kilometers between origin and destination.

Walk-only journeys are also included in the analysis, where this is within a 15-minute maximum journey time. In selecting this parameter, we attempted to reflect the potential impacts of reduced mobility, disability, and health on access to everyday destinations by walking and wheeling. As such, while we selected an average walking speed that may not be obtainable for many people with reduced mobility, we balanced this by capping the total ‘walk only’ trip to a relatively short distance (1 kilometer). This avoids distortions on the public transport interchanges which would have resulted from choosing a significantly lower walk speed parameter, while constraining the total access to destinations that this is likely to cause.

For car and public transport access, journeys were analysed for a:

- Tuesday morning, departing between 8AM and 10AM
- Tuesday evening, departing between 7PM and 9PM
- Saturday afternoon, departing between 12PM and 2PM

Metric development

At this stage, we converted our access modelling outputs into access metrics. These metrics, and the process for developing them, are summarised in the table below. Metrics were produced for each destination, time period, and mode combination previously defined. These metrics are then grouped and converted in the final stage to produce the access index.

Metric	Description
Reach	If one destination is reachable within a defined threshold. A 30-minute threshold was used for all destinations. This is not calculated for All Employers, with Large Employers being used to measure reach to employment.
Choice	The number of destinations reachable within a defined threshold. A 30-minute threshold was used for all destinations apart from All Employers. For All Employers, this is the number of jobs reachable, and was measured within both a 30 and 60 minute threshold.
Journey time	The journey time to the closest destination, capped at a maximum of 120 minutes.
Mode time gap	The difference between car and public transport journey time to the closest destination.
Period time gap	The difference between the longest and shortest journey time to the closest destination across the time periods measured.

Index development

The final stage is converting the set of access metrics into an access index. This is done in four categories – amenities (banks, supermarkets, town or retail centre), health (dentists, GP surgeries, major hospitals, pharmacies), education (primary schools, secondary schools, further education colleges), and work (all employers, larger employers).

Index	Description
Public transport reach	The percentile of the sum of the number of destinations reachable by public transport.
Car reach	The percentile of the sum of the number of destinations reachable by car.
Public transport time	The percentile of the mean percentile for journey time to each destination by public transport.
Car time	The percentile of the mean percentile for journey time to each destination by car.
Public transport choice	The percentile of the mean percentile of the number of destinations reachable by public transport.
Car choice	The percentile of the mean percentile of the number of destinations reachable by car.

These indices were then combined into a final access index as follows:

- For each category sum the six percentiles.
- Within each category, calculate the gap between the three public transport access percentiles and the three car access percentiles
- Within each category, subtract the gap between the car and public transport access percentiles from the sum of the six percentiles.
- Sum the score across the four categories.
- Convert the score into a percentile.

The percentile derived at the end of this process is then used as part of the TRSE risk calculation, by combining it with the vulnerability score described in the relevant methodological annex.

Appendix 3: Measuring TRSE using access and vulnerability

Background

TfN's TRSE tool combines a vulnerability analysis and access analysis to estimate the risk of social exclusion caused by a transport issues. Appendix 1 describes the development of this vulnerability index, and Appendix 2 the access index. This Appendix describes how these two indices are combined to estimate TRSE in V3 of the tool.

Our approach to combining access and vulnerability to measure TRSE in V3 of the tool has not changed since V2, with the exception of the level of analysis changing from 2011 lower-layer super output areas (LSOAs) to 2021 output areas. Through this, V3 provides significantly greater local spatial detail than V2, and requires fewer generalisations to be made about diverse populations and access conditions within neighbourhoods.

More significant methodological improvements have been made in our approach to measuring access and vulnerability, as set out in Appendix 1 and 2. The focus in this has been to bring data up to date, incorporate a wider range of destinations and time periods, and better reflect different contributors to vulnerability. These changes are not discussed further in this Appendix.

Our approach to measuring TRSE

As in V2, V3 of the TRSE tool presents data in two ways:

- First, we measure the size of the population that it is at high and very high risk of TRSE on the national level, and identifies which OAs are in these categories. TfN uses this to monitor progress towards one of the strategic ambitions in our 2024 Strategic Transport Plan. This enables comparisons between regions and Local or Combined Authority Areas, but it is less able to identify variations within Local and Combined Authorities.

- Second, we provide a percentile for TRSE risk in each OA, in the context of a Local Authority, Combined Authority, or nationally. This is intended to support Local and Combined Authorities, national government, and other transport bodies in understanding how the risk of TRSE varies in specific local contexts. This enables highly localised comparisons, appropriate for all contexts.

Identifying high and very high risk areas

To identify nationally high and very high risk areas, we use the simple threshold approach that we applied in V1 and V2. Within this, we define high and very high risk OAs as follows:

- **High risk:** In the bottom 50% of the national distribution for both access and vulnerability. This applies to the total population of the OA.

- **Very high risk:** In the bottom 30% of the national distribution for both access and vulnerability. This applies to the total population of the OA.

The table below provides five examples of how we classify Oas according to their level of access and vulnerability:

Access percentile	Vulnerability percentile	TRSE risk category
10th	25th	Very high risk
15th	35th	High risk
35th	40th	High risk
55th	20th	Lower risk
60th	80th	Lower risk

Identifying local risk variations

Our approach to measuring TRSE risk within Local and Combined Authority is to first produce a score based on the national access and vulnerability percentiles for an OA, and then to produce a rank and percentile specific to the Local or Combined Authority area. This score includes an adjustment based on the gap between access and vulnerability, and is calculated as follows:

$$\frac{\textit{Vulnerability percentile} + \textit{Access percentile} - (\textit{maximum percentile} - \textit{minimum percentile})}{2}$$

As with our approach to identifying nationally high and very high-risk areas, our intention here is to identify OAs where social exclusion is caused specifically by transport. Because of this, we adjust the total by the gap between access and vulnerability percentiles, so that areas with the highest risk are those with both of these issues in combination.

The table below provides five examples of this calculation:

Access percentile	Vulnerability percentile	Percentile gap	TRSE score
10th	25th	7.5	12.9
15th	35th	10	18.3
35th	40th	2.5	25.4
55th	20th	17.5	27.9
60th	80th	10	48.3