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An open access approach to mapping climate risk and vulnerability for decision-making: A case study of Birmingham, United Kingdom

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ABSTRACT

The global climate is changing, and local authorities must respond to changing climate risk to protect citizens and the urban environment in which they live. This paper presents an open access approach to map climate risk and vulnerability using Birmingham, the UK's second city as a case study. A Climate Risk and Vulnerability Assessment (CRVA) was co-created with Birmingham City Council to ensure the approach supports the organisation's needs, now and in the future. Using Geographic Information System (GIS) software, eleven geospatial datasets expressing physical, environmental, and social variables were combined to characterise holistic climate risk and vulnerability relative to the city boundary, where the higher the score, the higher the combined climate risk and vulnerability of an area. The resulting map (i) transparently evidences climate impacts across the city and the underpinning drivers, (ii) supports the prioritisation of interventions for those areas most at risk or vulnerable to climate change, (iii) supports the implementation of more climate-resilient development, and (iv) can be managed by stakeholders going forward for monitoring and evaluation purposes. While there are inevitable limitations in what can be achieved with an open access approach, the current CRVA can be considered a 'minimum viable product' that can be developed and improved iteratively in climate adaptation planning cycles. Its results can feed into broader policy agendas, such as national adaptation plans, adaptation reporting, just transition, and biodiversity net gain.

Practical implications

The climate is changing and built environment practitioners need to incorporate the changing climate and associated hazards into their operational processes to ensure that their infrastructure is resilient for the future. This paper presents a decision-centric method to map climate risk and vulnerability that uses open access datasets and a methodology that is commensurate with the skills, software, and resources of local authorities and similar organisations (e.g., small businesses, infrastructure owners and operators) who need to adapt to climate change.

Taking a decision-centric approach is beneficial when considering climate risk and vulnerability as there is deep uncertainty regarding future climate, meaning that acting now with the information that is available is a preferable approach as opposed to waiting for further information. That way, adapting to climate change can be agile and continually improved as new knowledge is incorporated into the process. The Climate Risk and Vulnerability Assessment (CRVA) approach described in this paper produces a 'minimum viable product'; i.e., what one needs to get started. The outputs are a useful baseline for stakeholders to build on and to measure against for climate change adaptation monitoring and evaluation purposes.

The methodology uses Geographic Information System (GIS) software to combine different geospatial datasets into scalar data layers with a common resolution and score range. These layers are subsequently summed to provide a total CRVA score, where higher scores indicate higher risk and vulnerability to climate change.

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The scores can then be averaged to geographical or political boundaries of interest. Here, we describe CRVA maps developed for use within Birmingham City Council (BCC). The approach is now being expanded and tested regionally in collaboration with the West Midlands Combined Authority.

The CRVA enables organisations to quantify relative risk across their constituent area and then factor this risk into decision-making, prioritise spending, support climate-resilient development, and measure and monitor changes to resilience across the city. For example, it could be used to select neighbourhoods most in need of increased green infrastructure due to a high risk and vulnerability to overheating, flood risk, and poor health outcomes, or for a local authority to review development proposals to ensure that they address and are designed for climate risks in the area. The method is also compliant with the Carbon Disclosure Project (CDP), a not-for-profit charity that runs the global disclosure system for organisations to manage environmental impacts. The CRVA outputs submitted by BCC to CDP based on this methodology resulted in the city receiving its first 'A grade' for transparency and bold climate action. Beyond the map, the CRVA method underpins the practice of iterative climate change adaptation planning, supporting broader policy agendas such as adaptation progress reporting, national adaptation plans and biodiversity net gain initiatives.

BCC has adopted the CRVA map as a new layer within their decision-making processes. It is currently in the process of reviewing the Birmingham Local Plan, which will determine the future planning policy for Birmingham for at least the next 20 years. A chapter is dedicated to Climate and Environment, where it will introduce the CRVA. BCC is also an active member of the global Biophilic Cities Network, an international grouping of cities who seek to put nature at the heart of their decision-making. BCC is liaising with Toronto, Canada over adopting their Green Standard approach. This Green Standard provides an accelerated route for developers to voluntarily take; above baseline planning policy to urgently address the climate and nature emergencies. The draft Birmingham Local Plan will be available in early 2025; with a first draft of the Birmingham Green Standard. The Birmingham Standard is predicated on the CRVA map of the city to determine the areas of greatest need to encourage prospective developers to opt for one of the higher voluntary climate and nature positive prescriptions.

To that end, this paper and its supporting documents describe an approach that can be adopted by any local authority in England, or UK (using devolved datasets) or globally, using the approach and locally relevant datasets.

Introduction

The global climate is changing (IPCC, 2021), but not everyone is equally affected by it, as climate risk is not wholly determined by climate hazards alone. Due to several past- and present-day environmental and socio-economic factors, there are substantial variations in the magnitude of people's vulnerability to the effects of climate change both among and within regions – including land use, inequity, marginalisation, and governance (IPCC, 2022). This inequality of climate risk exists across multiple spatial scales. Poorer and/or marginalised communities are often more negatively affected by the impacts of climate change as their existing vulnerabilities and inequalities are intensified (IPCC, 2022). On the international scale, countries in the global south (e.g., across Sub-Saharan Africa) are among those worst affected by climate change relative to the rest of the world, especially in terms of health outcomes (Levy and Patz, 2015). However, at the national, regional, or local scale, and even in developed countries, the inequality of climate impacts is noticeable in relative terms. Studies on the United Kingdom (UK) have shown that (i) social deprivation is a key vulnerability factor that exacerbates adverse health outcomes related to climate change (Paavola, 2017); (ii) lower income groups and other disadvantaged groups, while contributing the least to causing climate change, are disproportionately impacted by its effects (Preston et al., 2014; Sheng et al., 2023) and (iii) these same groups have fewer resources with which to adapt and are less able to participate in decision-making regarding broader societal responses (Preston et al., 2014). To address these inequalities through effective policy, decision-makers require the appropriate tools and resources to identify and prioritise interventions that promote climate-resilient place-making. Such tools and resources should consider the spatial dimensions of climate risk as a critical element of decision-making as they highlight localised inequity and provide an opportunity to tailor to the needs of and engage with those more at risk and vulnerable to the effects of climate change.

Mapping climate risk and vulnerability

Research related to climate risk and vulnerability has increased rapidly in recent years (Fig. 1). Improved data availability and quality over time has made it possible to synthesise multiple climatic, biophysical, and socio-economic data to communicate climate risk spatially and develop decision-support tools. As such, mapping climate risk and vulnerability can also help prioritise, target, and plan climate change adaptation investments tailored to the needs of places at the local level where the consequences are experienced more acutely (Preston et al., 2011).

Studies on Climate Risk and Vulnerability Assessment (CRVA) mapping benefit from a decision-centric approach as opposed to a science-first approach (Ranger et al., 2013), as it aligns well with delivering effective adaptation planning outcomes. However, outputs are usually both area- and problem-specific, influencing the nuanced detail in studies' methodologies. CRVA outputs may consider the local level e.g., divisions of an urban area (Lapola et al., 2019; Zhang et al., 2018; Greater London Authority, 2022) as well as at larger, regional levels e.g., divisions of a country (Heydari Alamdarloo et al., 2020; Leis and Kienberger, 2020; Azam and Rahman, 2022). A CRVA map was also produced for the United States of America encapsulating both the local and national scale (Tee Lewis et al., 2023). CRVA studies also have different foci and use different variables to identify the spatial dimension of climate risk and vulnerability. While many studies take a multi-hazard approach (Azam and Rahman, 2022; Kim et al., 2016; Murshed et al., 2021; Tee Lewis et al., 2023; Greater London Authority, 2022), there are others which focus specifically on a single hazard to address a particular problem such as: risk and vulnerability to heat (Ferranti et al., 2023; Todeschi et al., 2022; Maragno et al., 2020; Zhang et al., 2018; Aminipouri et al., 2016; Lapola et al., 2019); flooding (Leis and Kienberger, 2020; El-Zein et al., 2021); and drought (Heydari Alamdarloo et al., 2020).

CRVA maps support climate change adaptation planning cycles. Adapting to climate change should be an iterative process: scoping and parameters are defined, data collected and analysed, actions agreed and implemented from data findings, and then actions are monitored and evaluated to inform the next cycle of the process (Quinn et al., 2018; Greenham et al., 2022b). Having an iterative process is beneficial for several reasons. Firstly, it provides a means by which future uncertainties in climate impacts or socio-economic factors can be incorporated into planning, as each iteration allows for updates. Secondly, it allows for new technologies or approaches to be incorporated as they are developed. Finally, it allows for the outcomes of previous and ongoing adaptation efforts to be incorporated and used to support future adaptation actions. Mapping climate risk and vulnerability aligns well with iterative adaptation, as the practice of mapping CRVA is a method that is currently growing and maturing (de Sherbinin et al., 2019). Configured correctly using robust map layers, CRVA maps can be inherently flexible and be updated as input data changes, thereby incorporating ongoing or future changes in climate risk and vulnerability that are either positive (e.g., adaptation is reducing climate risk) or negative (e.g., climate

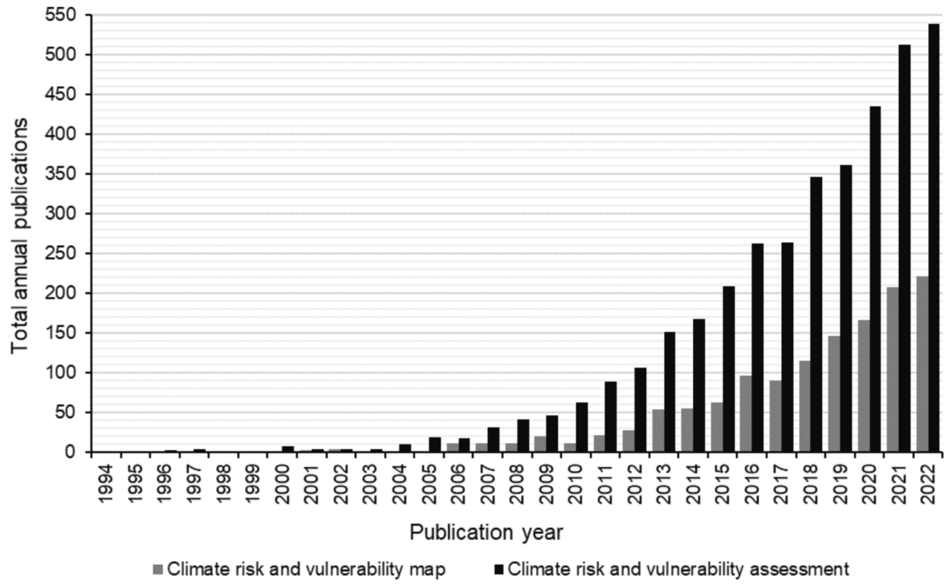

Fig. 1. Total annual publications 1994–2022 based on a keyword search of 'climate risk and vulnerability map' and 'climate risk and vulnerability assessment' according to the Web of Science database.

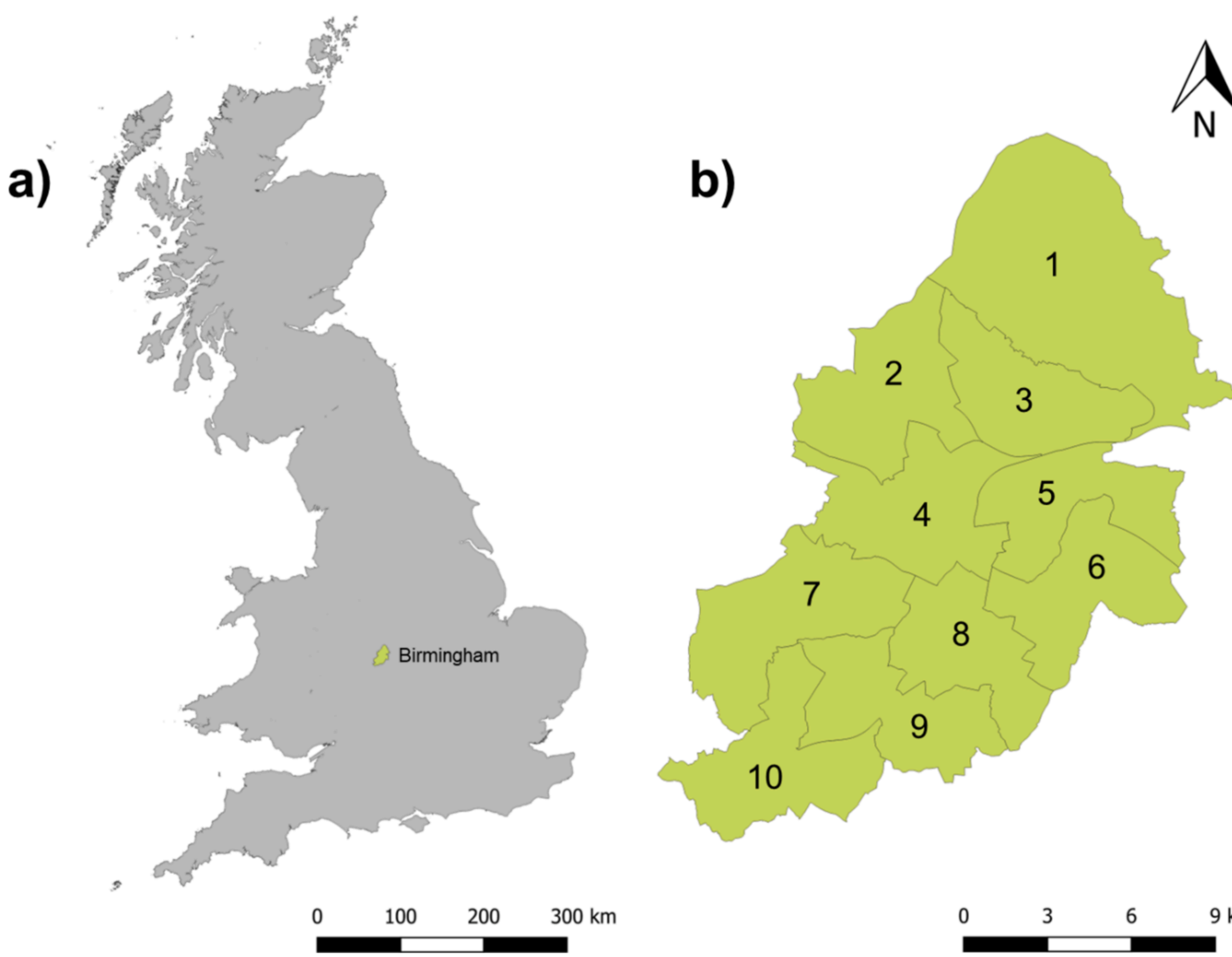

Fig. 2. Birmingham in the context of a) Great Britain and b) its Parliamentary Constituencies: 1. Sutton Coldfield; 2. Perry Barr; 3. Erdington; 4. Ladywood; 5. Hodge Hill; 6. Yardley; 7. Edgbaston; 8. Hall Green; 9. Selly Oak; 10. Northfield. Note that these boundaries are based on the 2019 UK general election and can be subject to change. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

impacts are worse that originally mapped).

The city of Birmingham and its progress towards a CRVA map

Shown in Fig. 2, Birmingham is the second largest city in the UK and has a population of 1.4 million people, with a young and ethnically diverse demographic profile (Office for National Statistics, 2023). Known as the *city of a thousand trades*, Birmingham has a strong industrial history, and rapidly expanded just before the start of the industrial revolution (Hopkins, 2002). The city was heavily bombed during the Second World War and subsequent development was car-oriented, and the large post-war housing estates and ring roads are thought to have negatively affected communities; reinforcing crime, isolation and disengagement (O'Farrell et al., 2020).

More recently, the city has strongly focused on sustainability, climate action, and the role of nature in creating liveable and climate-resilient places. The Big City Plan (Birmingham City Council, 2011) outlines ambitious greenhouse gas emissions reduction targets and commitments to be resilient to future climate change. As part of these commitments, Birmingham City Council (BCC) reports its environmental progress transparently through the Carbon Disclosure Project (CDP) that runs a global disclosure system for investors, companies, cities, states, and regions to manage their environmental impacts (CDP, 2023). BCC submits to CDP each year and in 2023 received an 'A grade' for the first time, following the submission of the CRVA described in this paper. Since 2022, climate resilience has been listed on the Corporate Risk Register, meaning all developments must consider future climate impacts and options to embed climate resilience. Birmingham is also a Tree City of the World (Birmingham City Council, 2020), it has its own Urban Forest Master Plan (Treeconomics, 2021), and the Our Future Nature City Plan will change how green space is managed by the city, addressing unequal access to green space, prioritising tree planting in areas of higher socioeconomic deprivation, and ensuring all parks in the city meet the Birmingham Fair Park standard (Birmingham City Council, 2022). Looking to the future, Birmingham hopes to be known as the *city of a thousand green spaces*. The CRVA developed in collaboration with BCC builds on this body of work, specifically mapping of environmental justice (Sultan et al., 2023) and prototype research mapping heat vulnerability (Ferranti et al., 2023).

Methodology

Like many other studies e.g., Yu et al. (2021); Aminipouri et al. (2016); Kim et al. (2016), The CRVA for Birmingham combined multiple spatially relevant data which are geophysical, environmental, and socioeconomic, into a standardised indicator. This study's CRVA outputs were formed of 11 separate data layers, which were aligned and normalised using the QGIS application to build a final CRVA map at 100 m resolution via raster map algebra. The results were subsequently aggregated into user-defined boundaries using zonal statistics. The approach is considered a 'minimum viable product' (MVP), that produces a map that can be used to support local authority decisions and can be replicated using the time and computing resources that are routinely available in local authorities.

Data

The data layers underpinning the CRVA map for Birmingham were primarily open access, with each data layer's details described in Table 1. Each data layer provides information about either the physical, environmental, or social characteristics of the area, all of which are indicative of an aspect of climate risk or vulnerability. The data variables selected to build the CRVA were based on expert judgement of the authors in consultation with stakeholders in BCC, with supporting literature to justify their inclusion in Table 1. Validation of datasets were undertaken via academic peer-review or managed by a government agency. Eleven data layers is fewer than most other studies but are considered to be MVP requirements – the literature reviewed which reported datasets or defined indicators used for respective CRVA maps ranged from 8 (Maragno et al., 2020) to 38 (Azam and Rahman, 2022). The CRVA map for London, UK could be considered the most comparable map in terms of scale and parameters to this study, which uses 13 layers (Bloomberg Associates, 2022).

Layer processing

Each data layer required processing to create a standardised format for combining into a CRVA score. As the underlying data for each layer varies, conversion processes for each layer also varied. Step-by-step processes undertaken for each layer in QGIS are described in Greenham et al. (2023). Fig. 3 shows a process flow overview for all the layers. First, each layer was reprojected to the same 100 m raster grid. This required the generation of a 100 m gridded vector of the Birmingham administrative boundary for reprojection algorithms; either through averaging higher resolution raster data (Nitrogen dioxide (NO_2) concentration, fine particulate matter ($PM_{2.5}$) concentration, and tree canopy cover deficit), a resampling of lower resolution raster data (surface temperature), or via a vector to raster transformation (the remaining vector layers). Next, each reprojected data layer was rescaled from a value of 0 to 1, where 0 reflects the lowest relative climate risk and vulnerability of a layer and 1 reflects the highest relative climate risk of a layer within the administrative boundary of Birmingham. For most layers, data were normalised into 20 quantiles with 0.05 intervals using a quantile generating algorithm, generating non-parametric outputs that when combined did not over- or understate outlier observations among the layers – particularly those with a wide range of continuous data observations (e.g., NO_2, $PM_{2.5}$, and excess years life lost (EYLL)). However, due to the skewed distribution of some layers, the results produced outputs that look more 'binary' (e.g., fluvial and pluvial flood risk, and open green space deficit). The exceptions to this process were the IMD layer, as decile values across the UK were readily available; and the local climate zone (LCZ) layer, as classifications were converted from a qualitative to quantitative format through expert judgement in a similar approach to Ferranti et al. (2023). A reclassification algorithm was conducted to reclassify raster cells accordingly. Finally, the raster calculator was used to sum the 11 normalised layers, without weightings, producing the final CRVA score. This final CRVA layer is a score for each 100 m cell between 0 and 11, where the higher the score, the higher the overall climate risk and vulnerability of the area. This final map therefore shows a greater distribution of cell values than the contributing map layers which are binned to 20 quantiles. Using the zonal statistics algorithm, the 100 m layer can be aggregated to show mean CRVA values (with standard deviations as to not overlook pockets of vulnerability within boundaries) for a range of administrative boundaries, such as Parliamentary Constituencies, Wards, and LSOAs.

As a MVP, the layers comprising the total CRVA score for Birmingham were unweighted. This means that all the layers contribute an equal amount to the total score, hence a maximum possible score of 11 for all the layers, which are each scored 0–1. There were several reasons for taking this approach. From a practical perspective, local authorities often experience capacity challenges and are limited in time and computing resource to conduct these assessments or update them; an unweighted approach is parsimonious, limits complexity, and avoids subjectivity. From a scientific stance, similar studies also took an unweighted approach (e.g., Allen et al., 2018; Maragno et al., 2020; Greater London Authority, 2022). Justifications included (i) a lack of detailed data or local studies (Allen et al., 2018); (ii) the risk of politicisation underpinning weighting decisions (Maragno et al., 2020), which also links to subjectivity (Luers et al., 2003); (iii) the possible variability in layer weightings according to different climate hazards (Maragno et al., 2020); and (iv) uncertainty in outcomes due to the methodological approach (Maragno et al., 2020; de Sherbinin et al.,

Table 1
Key characteristics of data layers used to build the CRVA map for Birmingham.

Layer	Source	Format	Unit of measure	Quality assurance	Reason for inclusion
Nitrogen dioxide (NO_2) concentration	2019 baseline model Zhong et al., 2024	10 m raster	Annual mean μg m^{-3}	Model evaluation undertaken by comparing measured data and using statistical and graphical methods (Zhong et al., 2024)	An air pollutant correlated with climate change as it is emitted from the same source (fossil fuel combustion), and therefore there are co-benefits in reducing air pollution (Im et al., 2022). High NO_2 exposure is linked to respiratory issues and an association with lung cancer (DHSC, 2022). Alternative, open data, but with a lower resolution (1 km) is accessible at DBEIS (2023).
Fine particulate matter ($PM_{2.5}$) concentration	2019 baseline model Zhong et al., 2024	10 m raster	Annual mean μg m^{-3}	Model evaluation undertaken by comparing measured data and using statistical and graphical methods (Zhong et al., 2024)	An air pollutant correlated with climate change as it is emitted from the same source (fossil fuel combustion), and therefore there are co-benefits in reducing air pollution (Im et al., 2022). High $PM_{2.5}$ exposure is linked to increased mortality and morbidity from cardiovascular and respiratory diseases (DHSC, 2022). Alternative, open data, but with a lower resolution (1 km) is accessible at DBEIS (2023).
Fluvial flood risk	(Environment Agency, 2022a, 2022b)	Vector Shapefile	% of raster cell covered by Flood Zone 3 and/or Flood Zone 2	Managed by UK Environment Agency	Climate change is expected to increase flood risk from rivers across the UK (Hanlon et al., 2021). In Birmingham, groundwater abstraction has fallen due to decreased industrial activity, increasing groundwater levels and thus fluvial flood risk (BCC, 2017).
Pluvial flood risk	(Environment Agency, 2021)	Vector Shapefile	% of raster cell covered by 3.3 % annual chance of surface water flooding	Managed by the UK Environment Agency	Medium and high impact rainfall days are expected to increase in in the UK (Hanlon et al., 2021), likely overwhelming drainage systems in built-up areas, so standing water is unable to drain effectively (WMCA, 2022).
Open green space deficit	(Ordnance Survey, 2022b)	Vector Shapefile	% of raster cell not covered	Managed by Ordnance Survey	Open green space can reduce the impacts of climate change as it has a cooling effect on the local environment, but also access to large, open green spaces has co-benefits including improved air quality, human health, and local ecosystem services (Bowler et al., 2010; Norton et al., 2015; Kingsley and Ontario, 2019).
Other green space deficit	(Ordnance Survey, 2022a)	Vector Shapefile	% of raster cell not covered	Managed by Ordnance Survey	Gardening practices in smaller green spaces, such as private gardens or community allotments in more densely built environments regulate the microclimate; cooling the air and lowering the urban heat island effect, as well as reducing surface flood risk (Humaida et al., 2023; Tomatis et al., 2023). Microclimate regulation is heightened when such green spaces are interlinked with others (Cabral et al., 2017).
Tree canopy cover deficit	(Environment Agency, 2022c)	1 m raster	% of raster cell not covered	Managed by the UK Environment Agency	Urban tree canopy plays a crucial role in thermal comfort regulation (Ornelas et al., 2023) and can also intercept precipitation, resulting in slower, more gradual surface runoff (Alivio et al., 2023), and reduced surface flood risk.
Surface temperature	(Met Office, 2022)	1 km raster	Maximum summer (JJA) temperature, 1981–2000, °C	Managed by the Met Office	High temperatures are a health risk, particularly for the most vulnerable such as the elderly (Hajat et al., 2010; Meierrieks, 2021), and urban areas are more susceptible to higher temperatures due to the urban heat island effect (Oke, 1973). Therefore, summer temperatures are most indicative of the highest risk across an urban area, using the national climate baseline period of 1981–2000.
Local climate zones	(Demuzere et al., 2019a)	100 m raster	Discrete classification (Greenham et al., 2023)	Accuracy assessment undertaken on test area pixels to evaluate classifications (Demuzere et al., 2019b)	Local climate zones (LCZs) are categorisations of distinct landscapes and are linked to important surface parameters (Demuzere et al., 2019b), and therefore to climate risks such as overheating and flooding.
Indices of multiple deprivation (IMD)	(MHCLG, 2019)	LSOA level data, joined to vector Shapefile	National decile rank *per* LSOA	Managed by the Ministry of Housing, Communities and Local Government	Disadvantaged groups facing greater social deprivation are disproportionately impacted by the effects of climate change (Preston et al., 2014; Sheng et al., 2023).
Excess years' life lost (EYLL)	Public Health England (PHE) (provided by BCC)	LSOA level data, joined to vector Shapefile	Total EYLL *per* LSOA, 2012–2017	Raw data managed by PHE, EYLL processing managed by BCC	As a measure of population vulnerability in health terms, EYLL provides an indication of where the local environment may be affecting people's health outcomes. Given that climate change exacerbates existing health problems (Paavola, 2017), EYLL may likely provide further indication of vulnerability to climate change.

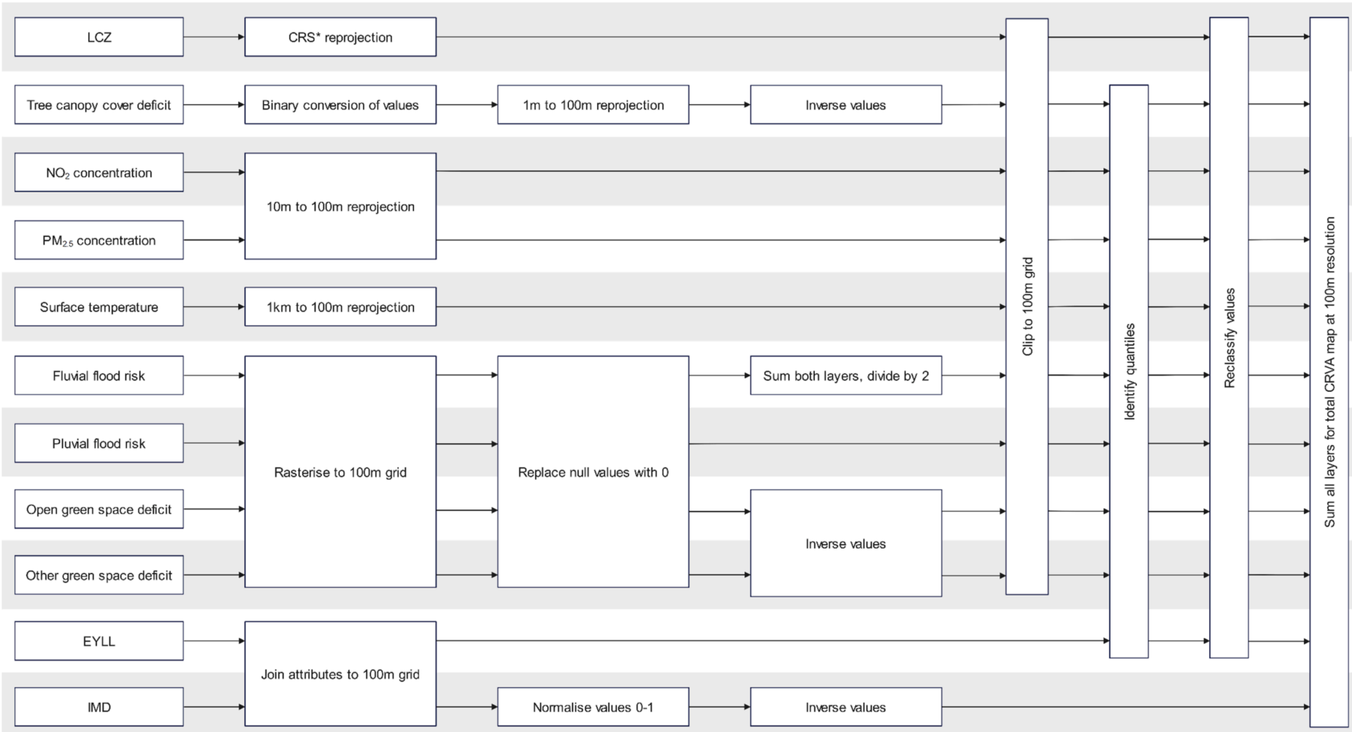

Fig. 3. Process flow diagram showing the transformation of each data layer into the combined CRVA map. *CRS = Coordinate Reference System; the LCZ raster product required converting from a European CRS to the British National Grid CRS to align with all other layers.

2019). Nevertheless, it is acknowledged that weighted approaches with greater statistical rigor can produce outputs with a more accurate and unbiased representation of the environment. Examples include utilising fuzzy logic modelling (University of Washington, 2023), principal component analysis (Azam and Rahman, 2022; Yu et al., 2021) and expert judgement (Leis and Kienberger, 2020).

Methods for further analysis

Using the suite of 100 m raster layers that form the final CRVA maps it is possible undertake further analysis to help characterise the areas within the city boundary for the benefit of stakeholders and decision-makers. For example, the underlying raster cell variables were used to generate a correlation matrix among all the different possible layer pairings. This identified the strength of relationships between two variables which could inform decision-makers regarding the cascading effect of changing one variable upon other variables, e.g., if additional green space or tree canopy cover can reduce overheating risk or flood risk. Additionally, descriptive statistics were obtained for each map layer by Parliamentary Constituency to show the spatial difference of scores across the city. Using these statistics provide quick-glance overviews of the potential drivers of climate risk and vulnerability at a spatial scale for the purpose of prioritising, tailoring, or designing climate risk interventions or adaptation actions. As a result, decision-makers can gain improved insight into whether certain climate risks or vulnerabilities are disproportionately influencing overall CRVA scores in particular areas. These outputs address the recommended direction of CRVA mapping to extend 'beyond the map' as the final product; using analytical techniques to draw out additional context which past research may not have previously undertaken (de Sherbinin et al., 2019).

Results

Firstly, Section 3.1 presents the eleven map layers comprising the combined CRVA index at 100 m cell resolution. Next, Section 3.2 shows the single CRVA map at 100 m resolution and by different administrative boundaries of Birmingham. Finally, Section 3.3 presents 'beyond the map' statistical analysis of the CRVA.

CRVA layers

Fig. 4 shows the scores of each data layer, which when summed, produces the total CRVA score. There are some similarities but also some differences among the layers. The air quality layers (annual mean NO_2 and $PM_{2.5}$ concentrations) show similar trends, where the city centre has the poorest air quality but NO_2 concentrations are more strongly associated with road networks while $PM_{2.5}$ is distributed slightly wider in higher concentrations across the city, particularly to the south. The flood risk layers (pluvial and fluvial) are more varied. The highest fluvial flood risk scores are very concentrated within the river networks whereas high pluvial flood risk scores are much more scattered, with small overlaps with high fluvial flood risk scores. There are bigger open green spaces north and south of an east–west band through the middle of the city, and the green space deficit is most prominent in the other green space layer through the city centre. Additionally, there is a large deficit of green space in the most northeastern part of the city. These are not built-up parts of the city (see the LCZ data layer) but are agricultural fields, which are not categorised as 'green space' from both green space deficit data layer sources. The tree canopy cover deficit data layer shows similar trends to both green space layers, implying that there is greater tree canopy cover in the presence of more green space cover across Birmingham. However, the surface temperature data layer's lowest scores are more skewed to the east than the centre compared with other data layers, which could be indicative of the effect of other geophysical factors such as prevailing wind or topography on temperature in the UK. The LCZ layer illustrates that most of Birmingham is built up, with the lowest open green space deficit scores matching the LCZ, and the highest scores running through a small and concentrated part of the city centre. The social data layers (IMD and EYLL) have some similarities, where

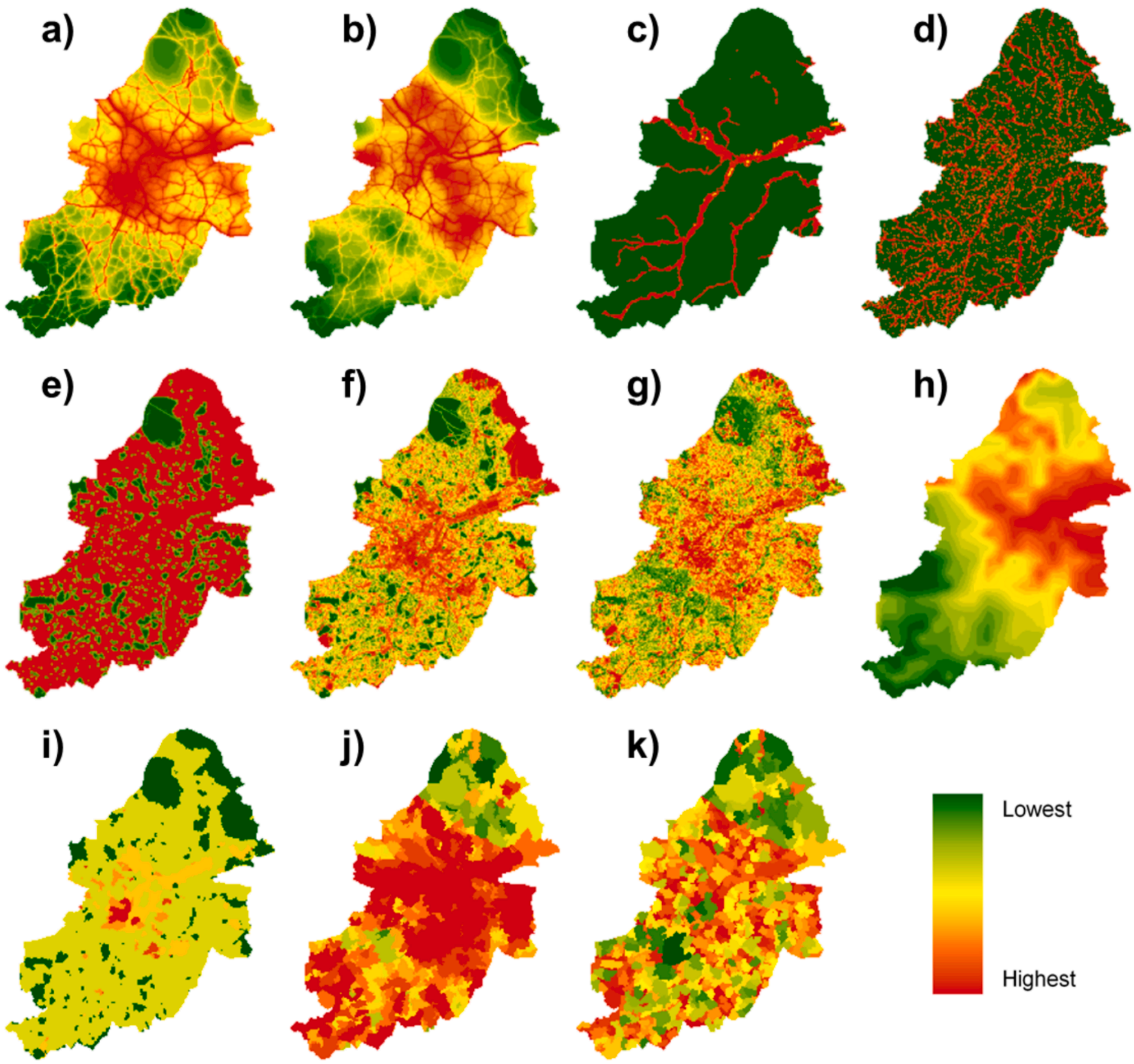

Fig. 4. Quantile binned scores of each data layer underpinning the total CRVA score: a) NO_2 concentration; b) $PM_{2.5}$ concentration; c) Fluvial flood risk; d) Pluvial flood risk; e) Open green space deficit; f) Other green space deficit; g) Tree canopy cover deficit; h) Surface temperature; i) Local climate zones; j) Indices of Multiple Deprivation; k) Excess years life lost. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

there is a clear divide in the north where scores are lower for the most part compared to the rest of the city. Scores are highest in the city centre and along parts of the southern boundary edges.

Combined CRVA map

Fig. 5 shows the combined CRVA map, which is the sum of all layers shown in Fig. 4. The lowest raster cell score was 0.95 and the highest was 10.25, highlighting a very broad score range across Birmingham. The city centre has the greatest share of high CRVA scores, which starts towards the east and then splits into high scores to the northwest and the south. In these areas, the fluvial flood risk is highest, there is the largest green space deficit, the LCZ scores imply that it is slightly more built up than its surroundings, and the air quality is poor. These characteristics are consequently likely to link with the lower social data layer scores, as the exposure to harm from climate risks is higher and there is limited infrastructure or actions in place to mitigate their effects.

By Parliamentary Constituency (Fig. 5a; see Fig. 2b for constituency details), there are clear geographical divides in the CRVA scores. The northernmost (Sutton Coldfield) and the four southernmost constituencies (Edgbaston, Hall Green, Selly Oak, Northfield) have fewer medium to high CRVA raster cell score coverage than the five middle constituencies (Perry Barr, Erdington, Ladywood, Hodge Hill, Yardley). The constituency borders correspond with some of the CRVA score divisions, suggesting that there may be physical attributes influencing these divides, such as a road, river, or railway line. In general, this CRVA map of Birmingham also shows that scores change gradually on a spatial scale; the lowest and highest scores are not located close to each other anywhere in the city. The same broad trends are also present when aggregated to LSOA (Fig. 5b) and Ward (Fig. 5c); climate risk and vulnerability are greatest through the middle of the city, decreasing in both north and south directions away from the city centre, with the overall lowest climate risk and vulnerability in the north.

Further analysis

Through extracting the raster cell variables for the Birmingham map, a correlation matrix was built to illustrate the statistical relationships between data layer pairings, shown in Fig. 6. Most of the data layer pairings have some extent of positive correlation within the city i.e., if a raster cell has a high score for one data layer, the score for the other data later is likely to be somewhat high as well. The strongest positive

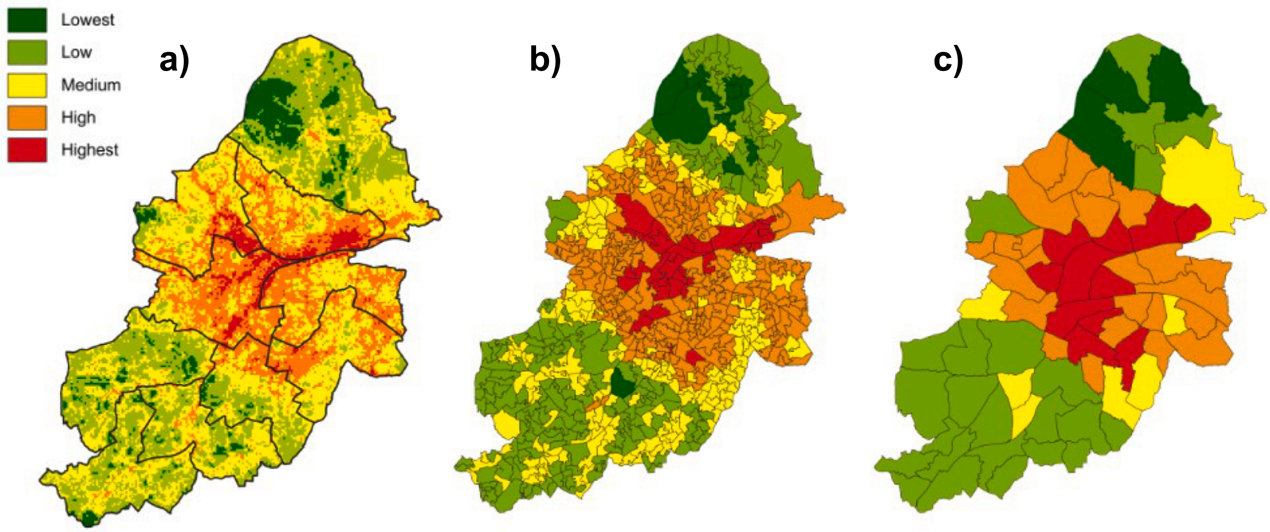

Fig. 5. The CRVA map for Birmingham at a) 100 m resolution (showing Parliamentary Constituency boundaries); b) LSOA boundaries; and c) Ward boundaries.

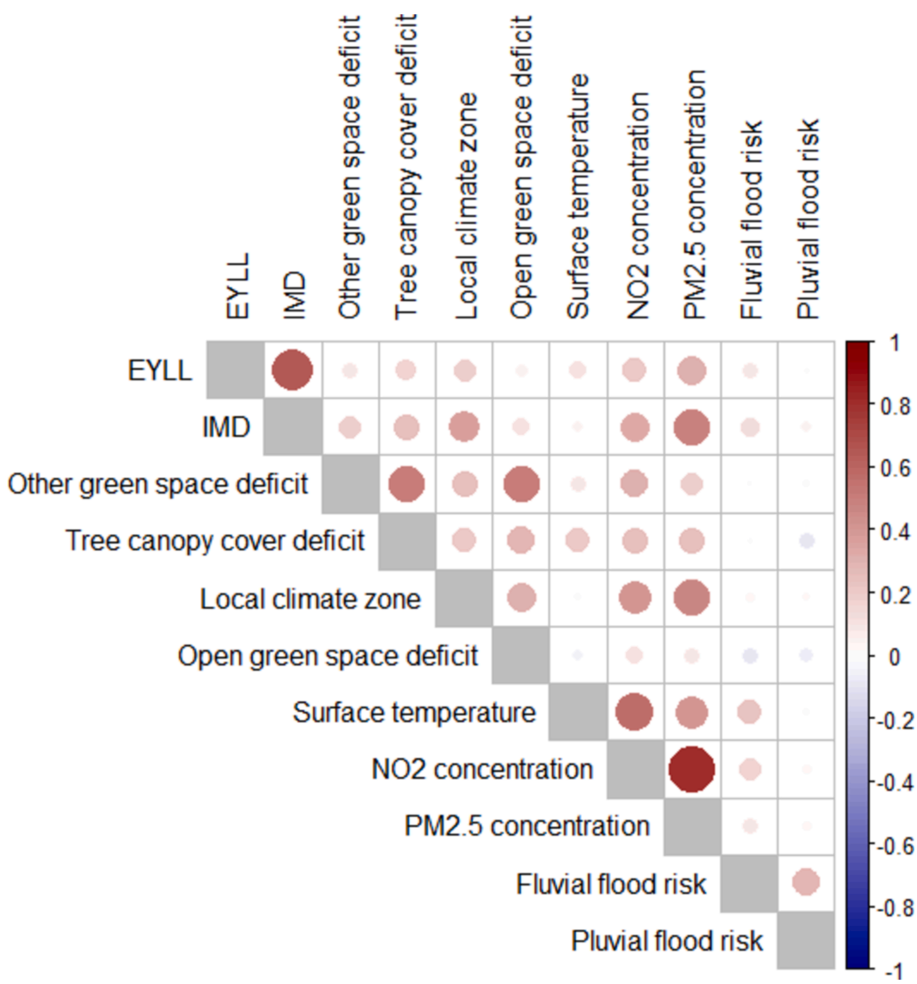

Fig. 6. Correlation matrix of data layer pairings of the CRVA for Birmingham. The larger and redder the circles, the stronger and more positive the correlation between the data layers (closer to R = 1); the larger and bluer the circles the stronger and more negative the correlation between the data layers (closer to R = -1).

correlation is between the air quality layers (NO_2 and $PM_{2.5}$), followed by EYLL and IMD, as well as open green space and other green space. These correlations were expected and indicate robustness in the mapping via the statistical methods applied, though also indicate that these layers may be duplicating similar climate risk and vulnerability attributes within the total CRVA score.

There are, however, other strong and positive correlations among data pairings that may not be explained by direct data overlaps – there may be a relationship, but it may not be a causal link. Firstly, while there were correlations between tree canopy cover and both green space layers, the correlation was stronger and more positive with other green space (all green areas) as opposed to open green space (those green areas that are publicly accessible). Secondly, $PM_{2.5}$ was more strongly correlated with IMD and LCZ than with NO_2. Thirdly, there was a stronger correlation between NO_2 and surface temperature than between $PM_{2.5}$ and surface temperature. Fourthly, the flood risk layers (pluvial and fluvial) did not correlate strongly with any of the other data layers, and it was strongest and positive with each other. Finally, there were negative correlations among pairings with the flood risk layers and both open green space and tree canopy cover, which is intuitive given the effect of trees and green space on reducing flood risk but may be countered to an extent by the effect of their proximity or concentration alongside rivers and areas of higher flood risk relative to other parts of the city.

Table 2 and Fig. 7 provide key statistical summaries of the CRVA scores at 100 m resolution by Parliamentary Constituencies. The descriptive statistics in Table 2 highlight the spatial difference in climate risk and vulnerability across Birmingham, but also within constituencies. Mean CRVA scores ranged from 4.17 (Sutton Coldfield) to 7.14 (Ladywood). Sutton Coldfield was also the constituency with the lowest minimum score of 0.95. However, Northfield had the lowest maximum score of 7.84. Hodge Hill had the lowest CRVA score range of 5.76, whereas Sutton Coldfield had the highest score range of 8.13. Standard deviations of scores for most constituencies were between 1.0 and 1.2. Those that were higher (Hall Green, Perry Barr, Sutton Coldfield) also had the highest CRVA score ranges, but varied substantially in the distribution of those scores across the constituencies. Therefore, each constituency has some level of climate risk and vulnerability to address.

To better understand the underlying factors affecting some of the spatial differences across the Parliamentary Constituencies in Birmingham, Fig. 7 shows the breakdown of mean score of each underlying layer of the total CRVA score *per* constituency. They were similar trends among the five outer constituencies (Edgbaston, Hall Green, Northfield, Selly Oak, Sutton Coldfield) and the five central constituencies (Erdington, Hodge Hill, Ladywood, Perry Barr, Yardley).

Of the outer constituencies, four of the five showed higher mean scores for IMD and open green space data layers relative to the others. The exception is Sutton Coldfield, where the open green space mean score was lower and surface temperature was higher, although this could be explained by geography; as Sutton Coldfield is the only outer constituency in the north. Nevertheless, while open green space scores may have been high, other green space scored lower – for most of these constituencies, the other green space mean score was almost half the open green space mean score. Both mean fluvial and pluvial flood risk scores were low across all five outer constituencies. Air quality scores were also low, although the scores in Hall Green were notably higher as an outer constituency, which could be due to nearby industrial estates and traffic on through roads leading in and out of the centre of Birmingham.

In the five central constituencies, most of the data layer scores were substantially higher. This applied particularly to IMD, as well as the air quality and green space data layers. All these constituencies also scored low for fluvial and pluvial flood risk. The only constituency with a slightly different trend across its mean scores was Ladywood. Both flood risk scores were slightly higher than the other constituencies, and its other green space score was substantially higher. Contrastingly, its mean surface temperature score was relatively low.

Table 2
Descriptive statistics of CRVA score by Parliamentary Constituency (see Fig. 2b for constituency details), based on data exported from the total CRVA map at 100 m resolution. Colour scaling demotes the largest (red) to lowest (green) values for each variable.

Parliamentary Constituency	Mean	Min	Max	Range	SD
Ladywood	7.14	3.02	10.20	7.18	1.20
Erdington	6.87	3.41	10.20	6.79	1.20
Hodge Hill	6.71	3.99	9.75	5.76	0.93
Yardley	6.26	2.99	9.79	6.80	1.09
Perry Barr	6.13	2.09	10.25	8.16	1.47
Hall Green	5.23	1.82	9.25	7.43	1.40
Selly Oak	4.71	1.62	8.24	6.62	1.08
Northfield	4.47	1.68	7.84	6.16	0.96
Edgbaston	4.30	1.28	8.40	7.12	1.08
Sutton Coldfield	4.17	0.95	9.08	8.13	1.39

Discussion

This paper introduced a MVP approach to assess climate risk and vulnerability using multiple geospatial datasets for the city of Birmingham, UK. By working collaboratively with BCC, the resulting CRVA map (i) transparently evidences climate impacts across the city and the underpinning drivers, (ii) enables the prioritisation of interventions by the most at risk/vulnerable areas of the city, (iii) supports climate-resilient development priorities, and (iv) can be managed and updated by BCC going forward for monitoring and evaluation purposes. The approach considers adaptation research for impact principles; including its co-production with users, emphasising societal impact and empowering actors for the long-term (Adaptation Research Alliance, 2021). Furthermore, the CRVA goal of capacity building for stakeholders engages with the 'Theory of Change'. In terms of climate adaptation, this includes the development of a stronger and more tailored evidence base that may increase access to funds that enhances climate resilience, particularly for the most vulnerable (Adaptation Research Alliance, n. d.). Nevertheless, there are limitations but also opportunities to the current CRVA mapping approach, which are discussed herein.

Data selection and handling

There are 11 data layers forming the CRVA map. These data were selected in accordance with expert judgement and local authority stakeholder consultation. Indeed, for BCC, the variables selected were considered of most importance to Birmingham, although these may differ in other cities or regions. The choice of data layers influences the CRVA score due to the synergistic effects of social, economic, and environmental factors, given the relationships between layers shown in Fig. 6 and also recognised in environmental justice mapping for Birmingham (Sultan et al., 2023). Weighting, and omitting some of, the underlying data layers of the CRVA scores could also address this, but as previously discussed, a non-weighted approach was justified in this instance from a parsimonious MVP perspective. Nevertheless, a weighted approach would be reasonable consideration, upon further consultation from stakeholders, specifically with more potential end users (de Sherbinin et al., 2019).

The data also determined CRVA map resolution; currently at 100 m. However, there remain potential inconsistencies in the results due to the processing methods and data themselves. For example, Ferranti et al. (2023) identified grid misclassifications at the very local level due, oftentimes due to methodological approach, as processes such as interpolation or averaging can introduce errors or spatial bias (Preston et al., 2011). Furthermore, some datasets used in this study include caveats that explicitly do not recommended interpretation at the household or dwelling scale e.g., Environment Agency (2022a, 2022b) as they are based on modelled data; being indicative rather than specific. As such, care should be taken when utilising the CRVA maps at the individual development scale for review or future scoping and planning.

This methodological approach focuses on observed data, and therefore there is not currently the capability to map future scenarios, which is a known limitation of such mapping approaches (de Sherbinin et al.,

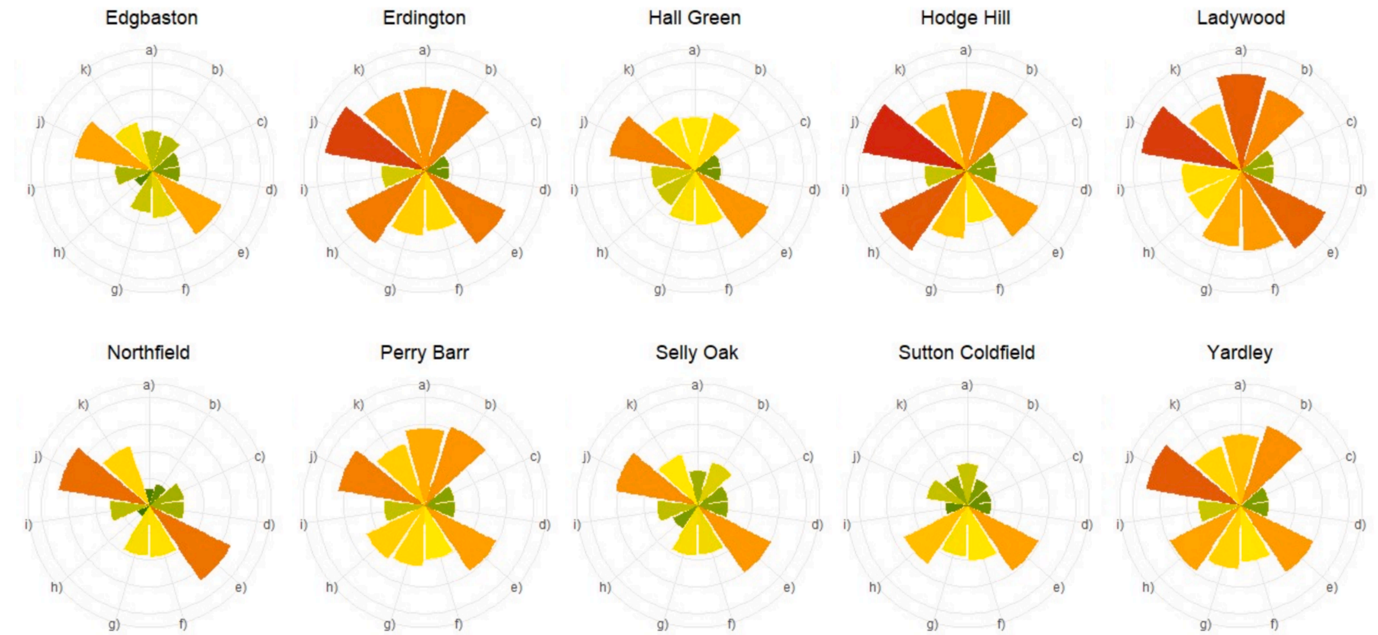

Fig. 7. 'Windroses' showing mean scores of each data layer *per* Parliamentary Constituency: a) NO2 concentration; b) PM2.5 concentration; c) Fluvial flood risk; d) Pluvial flood risk; e) Open green space deficit; f) Other green space deficit; g) Tree canopy cover deficit; h) Surface temperature; i) Local climate zones; j) Indices of Multiple Deprivation; k) Excess years life lost. The greater and redder the 'petal' the greater the average layers score, which contributes to a greater overall CRVA score for that constituency. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2019). Climate projection data are available, such as the latest UK-focused climate projection data (UKCP18) which was launched in 2018 and is frequently updated (Met Office, 2023) and can enable potential future scenario adjustments to CRVA data layers such as surface temperature and flood risk. The limitation with utilising these data in CRVA mapping, however, is that the spatial resolution of the projections is considerably lower compared to the observed data used (e.g., 5 km compared to 100 m). Furthermore, it also may not be possible to estimate future change across other data layers at an appropriate resolution. Indeed, high-level hypothetical future scenarios can be designed and implemented as 'thought experiments' (e.g., 50 % reduction in NO_2 due to traffic electrification, 20 % increase in tree canopy cover as a nature-based solution to climate change) but real future changes are unlikely to be equally distributed across the map boundary and such linear scaling somewhat undermines the local-scale design approach.

CRVA presentation, interpretation, and application

While there may be similar end-goals among research in this area, CRVA mapping methodological approaches are heterogenous (Preston et al., 2011) and results vary. Consequently, there are several considerations to make when translating CRVA outputs into actions, so that the risk of unintended consequences – such as maladaptation – are limited. These considerations can be categorised by the way the map is presented and interpreted, but also by application in more practical terms.

Regarding the presentation and interpretation of the CRVA map for Birmingham, it is important to note that results are relative to the city boundary to retain the focus on local needs. Data are binned only by observations within the boundary, meaning that results are not numerically comparable with areas outside the boundary. Different areas can, however, compare their relative exposure to risk (i.e., the distribution of areas of high, medium, or low risk recorded within each individual area). There are also implications due to this should a CRVA be extended to larger region, such as the West Midlands Combined Authority (WMCA). Doing so would require establishing new quantile bins, which would very likely affect CRVA results (i.e., the specific CRVA score for a particular place depends on the range of other places to which it is being compared). In addition, the data binning and normalisation process can mask data range extents for underlying data layers (i.e., a layer with a small absolute data range is normalised and scored 0–1 in the same way a layer with a larger absolute data range is normalised and scored 0–1). Stakeholders consequently need to be made aware of statistical methods affecting the layers. Aggregated maps should also be interpreted with care, as the averaging effect can mask the extent of underlying data's impact on an area (Table 2, Fig. 7).

Research that designs mapping tools to inform decision-making strongly advocates for their application in practice, for reasons such as improving local level analysis via enhanced resolution or data (Murshed et al., 2021); endorsing more accurate and sustainable urban design (Ngamsiriudom and Tanaka, 2023); and engaging with politicians (Opach et al., 2020). Moreover, research that demonstrates practical outcomes via mapping tools often engaged with stakeholders in the process, e.g., Opach et al. (2020); Canevari-Luzardo et al. (2017); Preston et al. (2009), showing that stakeholders add value to the tool development processes by ensuring it meets their needs, and the collaboration process contributes to stakeholder empowerment and capacity growth (Opach et al., 2020). Specifically for Birmingham, this began with the progress in environmental justice mapping underpinning Birmingham's Fair Park Standard (Birmingham City Council, 2022; Sultan et al., 2023). In developing the CRVA mapping for Birmingham, this paper contributes empirically to literature supporting adaptation planning practices which are collaborative with and simultaneously beneficial to stakeholders; working with policy makers so that outputs are geared towards them and their needs (de Sherbinin et al., 2019).

More broadly, applications of the CRVA can extend to policy contexts larger than its boundary. This method is compliant with CDP submission requirements which resulted in BCC's first 'A grade' submission in 2023 (Birmingham City Council, 2023), improving the city's reputation internationally. Stakeholders often consider mapping outputs to be helpful and easy to understand and the use of GIS not necessarily being perceived as a barrier (Canevari-Luzardo et al., 2017). Therefore, the inclusion of CRVA-type maps would provide greater accessibility of information to the public. They would be particularly powerful in publications with far-reaching impact such as the UK's national adaptation plan, the UK's climate change adaptation reporting power submissions or in biodiversity net gain reporting, which could also improve government accountability.

Monitoring and evaluation

This CRVA mapping approach has the potential to support monitoring and evaluation of decision-makers' progress in responding to and developing more climate-resilient places. This is crucial as the monitoring and evaluation aspect of climate change adaptation is a particularly challenging and sometimes overlooked part of the adaptation process. Low uptake or planning of monitoring and evaluation activities is experienced worldwide, and at a range of scales: it is reported across national adaptation plans in some of the lowest-income countries across Africa and South Asia (Greenham et al., 2022a), as well as across local government in developed countries such as Australia (Scott and Moloney, 2022).

Monitoring and evaluating climate change adaptation plans can be measured in three ways: (i) against the objectives of the intervention, (ii) against emerging understanding of good adaptation, and (iii) against a baseline (Pringle, 2011). The CRVA approach in this study considers a baseline approach. Once a baseline CRVA map is established, any change to underlying data layers can be incorporated to update CRVA scores in accordance with the baseline quantile breaks. However, updating the CRVA map would be dependent on updated data from its providers. As data updates could occur different times or intervals for each data layer, updating the CRVA could be intermittent, and not necessarily a true reflection of the holistic change in climate risk and vulnerability of an area. Any monitoring and evaluation action would need to consider this limitation. Furthermore, there is the added complexity of shifting baselines in future, or whether the current metric is fit for purpose e.g., in the case of this CRVA, an improvement in the quality of green space could be perceived as a more successful outcome as opposed to improving the green space deficit itself (Brown et al., 2018).

The ownership of updating a CRVA map for monitoring and evaluation purposes would most suitably lie with the decision-makers, providing there is both the technical and human capacity to do so. This is so that decision-makers have the freedom and flexibility utilise the CRVA as they see fit. Furthermore, with an open-access approach, there is a lower financial burden on decision-makers from at least a data acquisition perspective, as organisations such as local authorities often face financial capacity challenges.

Conclusion and forward look

The CRVA approach presented in this paper for the city of Birmingham, UK, demonstrates how open access data can be used to deliver a comprehensive overview map of climate risk and vulnerability, as well as multiple ways to present and interpret the data that benefits decision-makers such as local authorities. The approach is unique in the context that it was co-created with local government stakeholders across several departments and can now be managed and updated by them.

The methodological approach to the CRVA builds on established literature; using quality-assured datasets that are combined to quantify risk relative to the city boundary with a decision-centric approach as opposed to a science-first approach. By doing this, CRVA features can be improved upon across several aspects such as resolution, data weighting considerations, or the inclusion of future datasets. This is important as CRVA outputs should be considered as part of an iterative process of climate change adaptation. Underpinning this would be the utility of the map and the accuracy of the underlying datasets being reviewed at regular intervals to drive forward improvements in understanding risk, and the development of decision-centric support tools.

Looking forwards, CRVA mapping could be adapted to support other decision-making processes. While this paper describes a holistic CRVA of the built environment with consideration to citizens, there is scope to adjust the datasets and methodological approach for different outcomes, such a CRVA of an infrastructure type such as a transport network, or of variables that impact biodiversity. The underpinning principles to build a CRVA map remain, but the processes would require some level of change. Increased technical capacities owed to CRVA co-development could ultimately enable stakeholders to achieve greater climate resilience more extensively in their organisation.

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CRediT authorship contribution statement

S.V. Greenham: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **E.J.S. Ferranti:** Writing – review & editing, Methodology, Conceptualization. **S. Jones:** Writing – review & editing, Visualization, Methodology. **J. Zhong:** Writing – review & editing, Methodology. **N. Grayson:** Methodology, Conceptualization. **S. Needle:** Methodology. **W.J.F. Acton:** Writing – review & editing, Methodology. **A.R. MacKenzie:** Writing – review & editing, Supervision, Methodology. **W.J. Bloss:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Most data used are open access and referenced throughout, but some have restricted access and cannot be made available by the authors.

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