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Understanding and Assessing Climate Change Risk to Green Infrastructure: Experiences from Greater Manchester (UK)

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Abstract: The existing body of research into the environmental and socio-economic benefits of green infrastructure supports the case for it to be positioned as a form of critical infrastructure, particularly in urban settings. It is broadly recognized that extreme weather and climate change pose significant risks to critical infrastructure systems linked to the provision of services, including electricity, water, communications, and transport, and consequently risk assessments and associated adaptation strategies are common practice. However, although green infrastructure is also at risk from extreme weather and climate change, threatening the realization of benefits that it can deliver in urban settings, associated risks to green infrastructure are not widely understood or assessed in practice. This paper discusses the status of existing research on this topic and uses this as a foundation for a Greater Manchester (UK) case study that assesses the risk of low water availability to grassed areas, which represent a key element of the city-region's green infrastructure. In doing so, the paper demonstrates how risks linked to extreme weather and climate change can be assessed spatially to inform green infrastructure planning. In summary, this paper aims to raise awareness of extreme weather and climate change risk to urban green infrastructure, present an empirical case study and associated methodological approach on this topic, and ultimately support efforts to enhance the resilience of urban green infrastructure to extreme weather and climate change.

Keywords: extreme weather; climate change; climate change risk; climate change risk assessment; green infrastructure; urban areas

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1. Introduction

Climate change and associated extreme weather events are placing excessive strain on the longevity and functionality of urban infrastructure [1]. The greater frequency and extremity of flood, drought and heatwave events is testing the resilience of the built environment, as well as that of the environmental systems that support urban areas. Consequently, traditional investment options focused on the delivery of man-made "built" infrastructure are being reconsidered with a greater emphasis now placed on the delivery of green infrastructure (GI). GI can be defined as "… the network of green (and blue) spaces that conserve natural ecosystem values and functions and provide associated benefits to human populations" [2]. GI, and related concepts including Nature-Based Solutions (NBS), are presented in the research and practitioner literature as offering novel solutions to the complex problems of infrastructure redundancy, urban expansion and contraction, and ecosystem functionality within the context of a changing climate [3,4]. Accordingly, it has been suggested that rethinking GI (and NBS) as "essential infrastructure" comparable to grey/built elements of urban environments is needed as they support the delivery of diverse socio-economic and environmental functions that are critical to the successful working of cities and city-regions [5].

In an era characterized by an intensification of climate change and associated extreme weather events, GI is increasingly positioned as a crucial dimension of the adaptation responses needed to build climate resilience in urban areas [6]. However, a reluctance remains within urban planning and infrastructure debates regarding whether nature-led interventions can deliver the same reassurances in terms of their functionality when considered against built infrastructure [7]. These concerns have been exacerbated by a perceived lack of rigor in the socio-economic and ecological data used to underpin calls for investment in GI and NBS [8]. In addition to these critiques, there is an emerging debate linking discussions of infrastructure functionality in terms of failure/redundancy and the use of risk analysis techniques to increase the resilience of urban landscapes against extreme weather and climate change [9]. Indeed, there remains a limited holism with regard to climate change planning in terms of integrating considerations of risk, functionality, and novel data on ecosystem functionality [10].

Coupled with appreciating the variation of types and extent of ecosystem services attributed to GI, including how it can address climate change [11], there is also a need to better understand how extreme weather and climate change may impact on the efficacy of GI to deliver such services. It is here that the key contribution of this paper is situated. The first objective is to discuss the status of academic literature on extreme weather and climate change impacts and risks concerning urban GI. Although related studies are emerging, particularly in the context of urban trees and forests, this remains an under-researched topic with very little attention paid to concepts of climate change risk and risk assessment. The review of existing academic literature provides a platform for an empirical case study focused on assessing risk to Greater Manchester's (GM's) grasslands from low water availability conditions, the results of which are discussed from the perspective of how risk assessment outputs can be utilized to inform GI planning in this context. The risk assessment methodology applied within the GM case study is transferable. Given the availability of appropriate data sources, it can be applied in other contexts to advance knowledge of, and responses to, extreme weather and climate change risks to GI. This paper concludes that assessing extreme weather and climate change risk to urban GI should feature as an integral element of urban GI (and NBS) planning, practice and research to help maintain the provision of beneficial ecosystem functions and services under changing climatic conditions.

2. Literature Review

GI is often associated with urban areas. Urban GI is wide ranging and encompasses, for example, urban trees, smaller scale interventions, such as green roofs and walls, parks and gardens, and larger scale urban forests and river corridors that extend within and across urban boundaries. Urban GI provides ecosystem functions that support the generation of ecosystem services [12]. Ecosystem functions linked to urban GI include, for example, intercepting rainwater and evapotranspiration from vegetation. Ecosystem services arise from ecosystem functions, in this case including reducing flood risk and cooling air temperatures and require human beneficiaries to be classified as "ecosystem services" [13,14]. Ecosystem services linked to GI also make a significant contribution to the enhancement of human wellbeing [15].

European Council Directive 2008/114/EC [16] informs the identification, designation and protection of critical infrastructure. Article 2 of the Directive defines critical infrastructure as "...an asset, system or part thereof...which is essential for the maintenance of vital societal functions, health, safety, security, economic or social well-being of people, and the disruption or destruction of which would have a significant impact...as a result of the failure to maintain those functions." Given its inherent multifunctionality, there are calls for GI to be regarded as a form of critical infrastructure, for example, in the context of the contribution that it can make to disaster risk reduction [17]. Indeed, the release of the Institute of Chartered Engineers (ICE) Blue-Green Infrastructure Manual [18] explicitly called for GI to be treated as essential infrastructure to address these issues (see also [5]).

Huddleston et al. [19] use the term 'critical green infrastructure' to refer to natural and built environmental features that offer ecosystem services. This perspective is finding its way into practice, with Manchester City Council's Green Infrastructure Strategy noting that GI is as important to the city as other forms of infrastructure, such as transport, energy, and water [20].

Although GI is viewed as offering transformative potential to cities and urban areas, multiple factors act as constraints on realizing related outcomes in practice. These range from political reluctance to support novel nature-based approaches to climate change mitigation and adaptation [21], a lack of policy or legislative support for investment in greener projects in comparison to built infrastructure [22], a lack of availability of land to develop GI/NBS [6], the perceived capital cost of intervention and revenue costs of maintenance of GI/NBS [23], a lack of awareness from communities of the socio-economic and ecological benefits of GI [24,25], and the lack of technical knowledge in terms of the design, implementation and design of GI/NBS [26]. A canon of literature exists examining each of these issues.

Amongst the range of different constraints that threaten the expansion of urban GI and the delivery of associated ecosystem functions and services, levels of awareness and understanding of the risks that climate change and associated weather extremes poses to GI remains relatively low. Indeed, Huddleston et al. [19] identify that studies focusing on adaptation to climate change in the context of GI and NBS tend to see these forms of infrastructure as a component of physical adaptation measures targeted towards making other forms of critical built infrastructure more resilient to extreme weather and climate change impacts. Here, it is the role of GI in reducing climate risk that is the focus of attention, not the risk of climate change to GI itself. This perspective aligns with the broad range of academic research exploring the contribution of urban GI in adapting to climate change and extreme weather impacts [27].

Nevertheless, studies exploring how climate change may impact urban GI are emerging, with key themes synthesized in the following paragraphs. This discussion helps to raise awareness of what remains a relatively under-researched topic, whilst also setting the context for the empirical case study on risk to Greater Manchester's (GM) grassed areas from low water availability conditions. Indeed, although there are studies on how perennial grasses can be adapted to changing climatic conditions [28], research specifically on the impacts of and risk to urban grasslands from extreme weather and climate change is rare. However, one area of study that does connect to urban grasslands in this context concerns research on the relationship between high temperatures, reduced water availability, and the provision of cooling functionality through GI. Here, soil moisture plays an important role, influencing GI functionality and the extent of evaporative cooling from soils themselves [29]. Gill et al. [30] found that soil water deficits may arise in GM as the climate changes, with low water availability subsequently putting pressure on the ability of amenity grasslands to support urban cooling. Similarly, Jacob et al. [31] found that maintaining evaporative cooling functions provided by GI in Dutch cities requires adequate water supplies and that, with more frequent climate change induced droughts, the amount of water available to meet different needs, including maintaining urban GI, may be reduced. This issue has also been explored in Seoul, for example, where urban greenspace water demand is projected to increase with climate change [32].

Although research on urban grasslands is rare, there is also a growing body of literature focused on understanding how climate change and extreme weather affects urban trees. Trees and urban forests are an important component of urban GI, offering multiple ecosystem services [33]. Water deficit stands out as a key factor limiting urban tree health, resulting in crown and branch dieback and a reduction in associated ecosystem service provision [33]. Focusing on the US state of Indiana, Reynolds et al. [34] note that climate change is projected to change the species composition of its urban forests and will influence the services and disservices that they provide. Moreover, Sanusi and Livesley [35] established that, following a heatwave event in Melbourne, a 30–50% reduction in Plantanus x acerifolia leaf cover (a tree commonly planted in temperate and Mediterranean urban areas) was observed. Further, Dale and Frank [36] found that warming increases herbivorous insect pest fitness and abundance in urban forests, and that drought-stressed urban trees exhibit higher sugar and nitrogen concentrations that, in turn, make them more attractive to these pests. Research also suggests that the pace of urban tree growth is increasing across cities in different climate zones, driven by climate change-induced warming [37]. This is increasing carbon sequestration and tree growth above and below ground, potentially bringing forward the provision of ecosystem services. However, this is also problematic, as accelerated tree ageing brings forward the timeline for replacement [37].

The concept of risk has become fundamental to understanding and progressing climate change adaptation and is integral to successive assessment reports published by the Intergovernmental Panel on Climate Change (IPCC) [38]. The IPCC state that, "In the context of climate change impacts, risks result from dynamic interactions between climate-related hazards with the exposure and vulnerability of the affected human or ecological system" [38]. According to the IPCC's approach, climate risk can be understood as a function of weather and climate hazards (e.g., floods, droughts, heatwaves), the degree to which a human or ecological system is exposed to a specified hazard, and the vulnerability of the system to the hazard should it be exposed to it. Vulnerability is broken down into sensitivity and adaptive capacity themes, where sensitivity concerns susceptibility to harm from a hazard and adaptive capacity relates to ability to cope and adapt to impacts resulting from hazards. The IPCC's latest risk framework incorporates adaptation responses as a means of modifying or controlling the determinants of climate risk [38].

Risk concepts and assessment approaches are commonly applied within natural hazard and climate change adaptation across sectors and spatial scales [39–42]. Framing and assessing risks can inform the development of adaptation responses, enabling related decision making to be, "... iterative and support dynamic adaptive pathways through time" [38]. Risk assessments can also help to build knowledge and awareness, for example, by highlighting uncertainties that face decision makers [43] and illuminating the complexities that characterize the non-linear social-ecological systems that they look to intervene within. Indeed, as the IPCC note, "The determinants of risk all can vary and change through space and time in response to socio-economic development and decision making" [38]. Further, in addition to informing the prioritization of risks to focus on within climate change adaptation and resilience planning, risk assessments can also assist in targeting the allocation of resources towards the reduction of prominent climate risks [44].

Climate change and extreme weather events pose risks to critical infrastructure assets and networks and the provision of related services, with Huddleston et al. [19] stating that "The criticality of these systems should make them a high priority in climate change adaptation efforts". Recognizing these issues, climate change risk assessments have been a feature for several years. For example, in the UK, the Climate Change Act of 2008 requires critical infrastructure providers including utilities—water and electricity organisations and transport infrastructure providers, e.g., Network Rail and Highways England—to prepare climate change risk assessments. From a research perspective, studies are assessing climate change risk to different forms of critical infrastructure [43,45,46]. However, research into the risk of climate change and associated weather extremes to urban GI is rare. One notable exception is the study of climate change risk to urban forests discussed by Esperon-Rodriguez et al. [47], who assessed 3129 tree and shrub species within 164 cities across 78 countries from this perspective. Here, risk was evaluated as the difference between two factors, exposure and safety margin.

Goodwin et al. [27] note that, in the context of urban adaptation to climate change, action is needed to "...leverage the transformative potential of urban NBS". Although GI (and NBS) has the potential to support the achievement of urban adaptation goals, GI is itself also at risk from the changing climate. This threatens the delivery of a wide range of ecosystem services, including those linked to climate change adaptation. Building on existing research in the fields of urban GI, climate change adaptation and climate change risk assessment, and utilizing a case study focused on the risk of low water availability conditions to GM's urban grasslands, this paper addresses a gap in academic research concerning understanding and assessing climate change risk to urban GI.

3. Materials and Methods

3.1. Case Study Scope and Focus

A case study focused on GM, concerning assessment of the risk from low water availability to grassed areas across the city region, provides the empirical basis of this paper. GM encompasses a diverse landscape with a wide land cover gradient moving from a dense urban core through to peri-urban and rural areas, with amenity grassed areas commonly found across the city-region (Figure 1) [48,49]. This landscape presents the opportunity to explore the spatial variability of risk from low water availability to this GI type. As existing literature often focuses on the drought tolerance of urban trees [50–52], grass was selected as the GI type to expand learning on this topic, which remains under−researched. Further, trees often have greater root depth than grass, and usually have more ability to prevent water loss during conditions of low water availability than grasses, for example by closing their stomata [53,54]. Hence, during dry periods, grasses are more susceptible to harm from conditions of low water availability, which can lead to a loss of associated ecosystem functions [30]. Climate change projections for GM point towards drier and hotter summers [55], with low water availability events potentially becoming more commonplace. To explore this issue further, 2018 was selected as the year to base the risk assessment process around. In June 2018, a high-pressure system sat over the UK bringing high temperatures and low rainfall, and although comparative data are not available for GM, 2018 was the UK hottest summer on record (going back to 1884) and the 15th driest on record (going back to 1862) [56]. Probabilistic projections indicate that summer temperatures like those experienced during 2018 will become significantly more common under future climate change conditions.

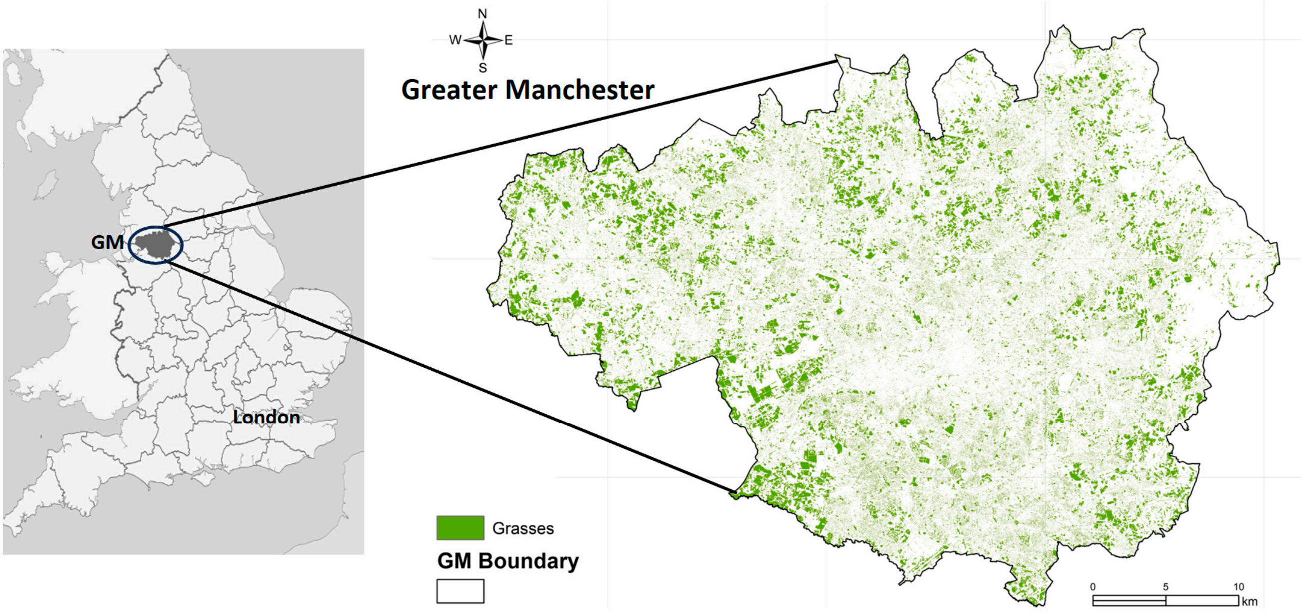

Figure 1. Study area location and grass area distribution in Greater Manchester. The input data of the grass was obtained from Dennis et al., (2018) [48]. The authors created the images.

3.2. Climate Change Risk Estimation for Grass

This study adopts the IPCC's risk assessment approach [38] to estimate risk to grassed areas in the GM region from low water availability conditions. It is the first study to apply this methodological approach to assessing climate change related risk to urban GI. This approach requires estimating risk based on Equation (1) below:

$$\text{Risk (R)} = \text{f (Probability of a Hazard (p)} \times \text{Exposure (E)} \times \text{Vulnerability (V))} \quad (1)$$

This function is operationalized within this study, incorporating hazards linked to disruptive weather and climatic conditions (in this case reduction in precipitation and consequently water availability) and the extent of exposure to hazards. Vulnerability to hazards, due to the sensitivity of the surrounding environment (in this case due to landscape fragmentation) and capacity to adapt to the negative consequences of detrimental hazard-exposure (in this case concerning access to groundwater to enable irrigation), is also incorporated. There follows an elaboration of the methods applied to spatially model risk to grassed areas in GM from low water availability based on this Equation (1).

3.2.1. Hazard-Exposure Assessment

Grass, and other forms of GI, require adequate water to maintain their physiological traits and to provide associated ecosystem functions, such as cooling from evapotranspiration. Hence, extended dry and hot summer periods represent critical hazards for grassed areas as the required amount of water cannot be extracted by the grass due to a deficit of water within the root zone [30]. Grass is more sensitive to a lack of water in comparison to trees. With declining surface water availability due to low precipitation, trees limit their evapotranspiration rate to adapt to these conditions whereas grass, with shorter and shallower roots, faces major challenges due to lack of water supply close to the soil surface [57]. Accounting for such aspects within this study, evapotranspiration induced by low water availability is the specific hazard considered for grassed areas in GM. The impact of this hazard is a function of exposure of grasses to low water availability, which in turn relates to the types and location of soil they are growing on [30,58]. As both aspects influence each other, low water availability and soil type were combined to spatially assess hazard exposure to all grassed areas within the case study boundary.

To assess hazard exposure, a simple Bucket water balance model was applied to estimate the amount of water available within the rooting zone of amenity grass and the related evapotranspiration ratio, as outlined by [30]. A detailed description of the Bucket water balance model is explained in [59] but, briefly, this approach estimates the actual evapotranspiration of grass by accounting for potential evapotranspiration, crop factor, and evapotranspiration ratio. In this case, evapotranspiration ratio (ERATIO) is a function of how much water is available for each soil type within the rooting zone of grass (RZAWC), soil water deficit (SWD) usually due to lack of precipitation, and limiting soil water deficit (LIMDEF), reflecting the minimum lower threshold availability of water for grass to extract.

HORIZON Hydraulics soil data for the study area were obtained from the National Soil Resources Institute at Cranfield University. This data provided the percentage volumetric water content of each soil type in our study area at 5200, and 1500 kPa suction levels. Using this data for each soil type (e.g., Alun, BELMONT, New Port) enabled the estimation of volumetric water content by the horizon thickness (up to the rooting depth of 50 cm), 15 cm depth for 5 kPa, 30 cm depth for 200 kPa and 5 cm depth for 1500 kPa suction. In this case, to estimate RZAWC, the volume of 5 k suction was subtracted from 1500 kPa suction, indicating the total amount of water available within the lowest and highest suction levels. LIMDEF was calculated by subtracting the water volume of 5 k suction from 200 k suction level, reflecting the water availability threshold within the first two zones of suction, where water is readily available, hence where evapotranspiration is maximized and beyond which water extraction makes it difficult for grass to perform normal evapotranspiration.

In addition, SWD was estimated using UK Met Office precipitation data for the GM area. As the water content of the soil is affected throughout the year by incoming precipitation and outgoing evapotranspiration, a lack of precipitation can cause SWD. Following [35], after the end of the winter recharge (in December 2017). soils are at field capacity at the start of April 2018 (within the immediate suction zone of 5 kPa), and therefore adequate water is available for the grass to extract. For the Greater Manchester case study region, SWD started from the month of April of 2018, with June 2018 selected as the month in which to estimate the SWD and thereby to evaluate the hazard exposure for grass. Precipitation records for each previous month up to April 2018 were obtained, where SWD was set to zero (no SWD in April, due to field capacity). Using Equation (2) below, we estimated SWD for each soil type for the case region:

$$\text{SWD for month (x)} = 0 \text{ or SWD month } (x - 1) - \text{Precipitation of month x} + \text{Potential evapotranspiration of month x}\ldots \quad (2)$$

Next, from May 2018, SWD was estimated considering the monthly average precipitation (taken as constant for the whole case study area), and potential evapotranspiration (PET) for grass for the whole study area for that month. PET for grass was then estimated based on historically observed (1961–1990) PET values from UK Meteorological Office records from Greater Manchester and then multiplied with the crop factor of grass used by [30]. This process estimated the amount of SWD due to incoming precipitation that month, outgoing evapotranspiration that month, and SWD from the previous month.

Finally, combining the RZAWC, LIMDEF, and SWD information for each soil type, the evapotranspiration ratio for grassed areas within the case study boundary was estimated. To conduct this analysis, the grass land cover location from 10 m resolution land use and land cover data created by Dennis et al. (2018) [48] were used, which identify grassed areas in GM. In this study it was assumed that these areas represent amenity grass types, which are the most common type found in the case study area [30,48], and include species such as Perennial Ryegrass (Lolium perenne), Chewings Fescue (Festuca rubra commutata) and Common Meadow Grass (Poa pratensis). For evapotranspiration ratio estimation, the RZAWC, LIMDEF and SWD information was first spatially joined with the grass patches using ArcGIS Pro (2.10) software. In this process, while joining the values to the grass layer, the 'maximum value' was considered for the joining rule. The maximum values of RZAWC, LIMDEF, and SWD found just underneath the grass area (polygons) were considered as RZAWC and LIMDEF for that section of grassed area. Using this information for the grass patch, the ERATIO based on Equation (3) below was estimated:

$$ERATIO = \begin{cases} 1, \ if \ SDW < LIMDEF \\ \\ \frac{RZAWC - SWD}{RZAWC - LIMDEF}, \ \ if \ SDW > LIMDEF \end{cases} \quad (3)$$

In this case, if SWD is below the LIMDEF, it was assumed that no loss of evapotranspiration was identifiable as the soil has enough water within the immediate vicinity of the grass roots to perform this function. Here, the actual evapotranspiration of grass would be equal to the potential evapotranspiration. In contrast, if SWD is greater than the LIMDEF, the evapotranspiration ratio was estimated based on the difference between total root zone water availability and SWD, divided by the difference between total root zone water availability and LIMDEF. The ERATIO values are between 0 and 1, where values close to 1 indicate limited loss of evapotranspiration capacity, and values near to 0 indicate near total loss of the evapotranspiration capacity needed to have actual evapotranspiration compared to potential evapotranspiration. This ratio (ERATIO) therefore measures the degree of water stress on grassed areas due to low levels of precipitation, which is a critical hazard impacting the evapotranspiration function of grass. The output of this assessment was considered as the hazard exposure layer for this risk analysis.

It should also be noted that, following [30] in calculating the SWD and ERATIO, the research ensured that SWD never became negative, meaning that the amount of water was not higher than the field capacity. The SWD value was therefore set to zero to mitigate any cases where negative values were identified. Additionally, checks were made to determine whether SWD was greater than available water content at the root zone. If this was the case, the SWD value was set to the maximum value of the available water content at the root zone. These checks ensured that SWD values reflected real-world conditions and did not therefore provide unreasonable evapotranspiration ratio estimations.

3.2.2. Vulnerability

In addition to the hazard exposure calculation, the vulnerability of grassed areas within the case study boundary to low water availability conditions was estimated based on two factors, the surrounding built-up area (which reflects sensitivity to low water availability) and groundwater depth (which reflects capacity to adapt to low water availability). These two factors were selected based on the outcomes of related studies [60]. Research indicates the potential impact of vegetation fragmentation in urban landscapes, driven by expansion of impervious built land cover, which in turn can reduce the water recharge capacity of soils and hence increase stress on vegetation [60,61]. Based on these considerations, the built environment density around grass patches was measured using the Sentinel-2 satellite-derived Normalized Difference Built-up Index (NDBI) for June 2018 to examine the built-up area density within 100 m of each grass patch [62]. Using the following Equation (4), the NDBI value at 20 m spatial resolution was calculated and used as a buffer analysis to aggregate the average NDBI value.

$$NDBI = \frac{\{SWIR(B11) - NIR(B8)\}}{\{SWIR(B11) + NIR(N8)\}} \ldots \tag{4}$$

Here, shortwave-infrared spectral range (SWIR) and NIR (near-infrared) bands were used to reflect the normalized built-up intensity values between −1 and +1, where high values near +1 indicate a very high-intensity built-up area. Further details of NDBI calculation approach can be found in [63].

Access to water for irrigation purposes can provide resilience to urban vegetation during extended periods of low water availability [64–66]. Accordingly, the potential for irrigation opportunities was selected as an adaptive capacity indicator for this study, with groundwater depth information for GM collected from the British Geological Survey [67]. These data provided spatially referenced point data on groundwater depth in the case study area, based on historical geological observations, which could potentially be accessed for irrigation purposes. An inverse distance weighted spatial interpolation method was applied to this point dataset to interpolate the groundwater depth for the entire case study area. Finally, the average groundwater depth was aggregated within 100 m of each grass patch.

3.2.3. Risk Assessment

The hazard exposure layer was combined with the vulnerability layers to estimate the overall risk to grassed areas in GM from the 2018 low water availability event. Layers were categorized into five classes using the natural breaks method to operationalize the risk estimation. For the hazard exposure layer, class 1 indicates the lowest loss of evapotranspiration due to low water availability and class 5 represents the highest loss of evapotranspiration. For NDBI values, the lowest built-up areas surrounding grass patches are represented in class 1, whereas the most highly built-up areas surrounding grass patches are assigned to class 5. For the groundwater depth adaptive capacity layer, class 1 represents the highest depth of groundwater from the surface, therefore reflecting lower adaptive capacity, as water that could potentially be used for irrigation purposes is more inaccessible. Class 5 indicates the presence of groundwater at the lowest depth from the surface, which can therefore be more easily accessed to irrigate grass patches. This classification approach enabled the different measurement units used for each risk layer to be organized into a consistent group of classes. After classification, Equation (1) was adopted to estimate the overall risk for the grass patches using Equation (5):

$$\text{Grass Risk} = (\text{ETo Loss} \times \text{Intensity of surrounding built-up areas})/\text{Groundwater availability}\ldots \quad (5)$$

In this case, the highest possible risk value is 25, and the lowest possible risk value is 0.2. Using the natural breaks method, risk values were subsequently grouped into five classes, ranging from lowest risk (class 1, very low risk) to highest risk level (class 5, very high risk).

3.3. Mapping and Analysis of the Risk Assessment Output

Mapping of the spatial distribution of risk classes, and the constituent hazard exposure and vulnerability classes, was completed for all of GM's grassed areas to identify patterns of risk arising from conditions of low water availability. Additionally, the risk assessment result was analyzed in conjunction with the socio-economic deprivation conditions of GM's neighborhoods. Socio-economic deprivation data from the English Indices of Multiple Deprivation (IMD) 2015 [68] (DCLG, 2015) were obtained for each Lower Super Output Area (LSOA), which have an average population of 1500–3000 residents in each LSOA. IMD is a composite of datasets linked to deprivation, and encompasses themes including income, employment, health, education and crime. The IMD data are organized around 10 classes, which enables spatial comparisons of relative levels of socio-economic deprivation. GM is diverse in this respect, and contains neighborhoods classified within the most and the least deprived IMD deciles (https://data.cdrc.ac.uk/dataset/index-multiple-deprivation-imd, accessed on 1 February 2024). In this analysis, the mean risk value for grassed areas within each LSOA was assessed using the spatial aggregation method in ArcGIS Pro. Finally, the difference in mean risk values for different deprivation groups was plotted using Box plot and tested using ANOVA test for associations between deprivation and risk to grassed areas in all of GM's LSOAs. The risk assessment and analysis results arrived at following this methodology are presented below.

4. Results

Figure 2 presents a spatial perspective of hazard-exposure related to evapotranspiration (ETo) loss for grassed areas across the GM case study area for June 2018, indicating that these grassed areas exhibit different levels of ETo loss driven by an extended period with no rainfall in June 2018 and SWD from April 2018. Spatial differences concerning the extent of ETo loss during this period are apparent. For example, the grassed areas in the northwestern region of GM show very high ETo loss. In contrast, grassed areas in the GM's southwestern region show low or very low ETo loss. This spatial variation resulted from the relationships between grass and different soil types based on water availability for each soil type within the rooting zone of grass (RZAWC) and the limiting soil water deficit (LIMDEF). For different soil types, we observed varying levels of RZAWC and LIMDIF (see Appendix A, Table A1), as each soil type possesses different water holding capacity within the rooting depth of grass. For example, soil types including "Winter Hill", "Turbary Moor" and "Longmoss" indicated high water content within the rooting zone, whilst "Crewe" and "Brickfield" soil types indicated very low water availability. Such differences are crucial and highlight that ETo loss and risk to grassed areas from low water availability is significantly influenced by the soil type that they are growing upon.

Figure 3 highlights the percentage of grassed areas falling within each of the five classes of ETo loss. Analysis indicates that approximately 62% of GM's total grassed area (approximately 129 km^2) displayed only 20% of their potential ETo for the month of June 2018. Therefore, during this period, actual ETo in these locations was considerably lower than the usual levels of potential ETo. Under these conditions, a considerable loss of ecosystem function (e.g., cooling from evapotranspiration) is experienced by grassed areas. This is because, under water deficit conditions, such as those experienced within this case study, grasses lower transpiration water loss firstly by curling up to reduce leaf surface area, then slowly wilt and ultimately turn to brown dry grass [69,70].

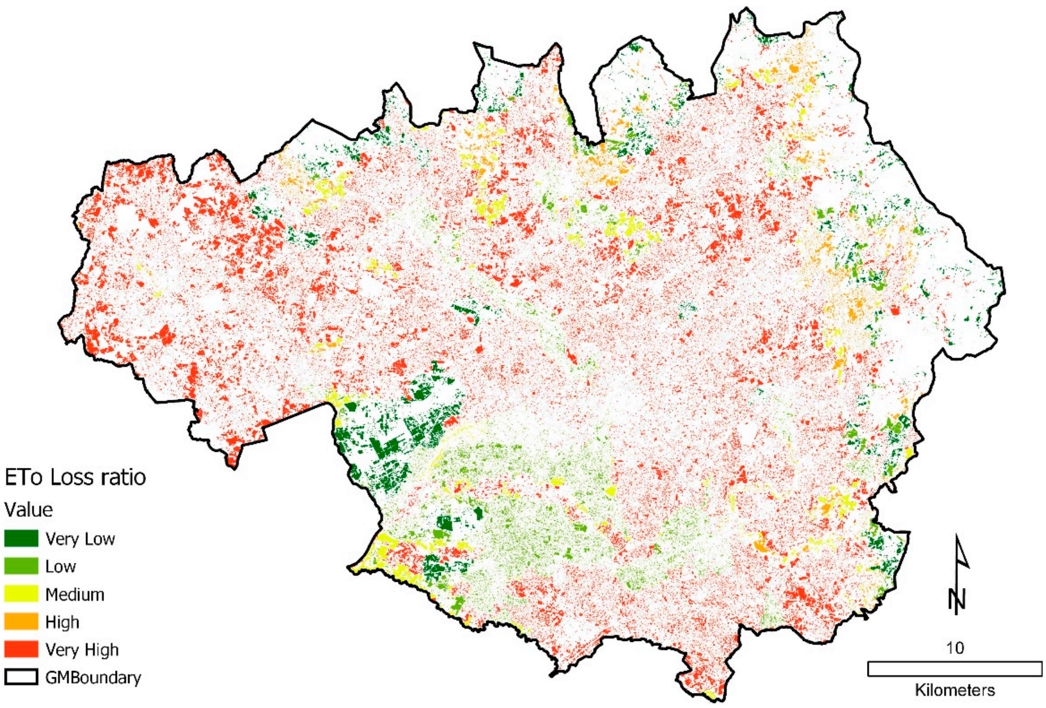

Figure 2. Spatially explicit ETo loss for grassed areas across Greater Manchester for June 2018.

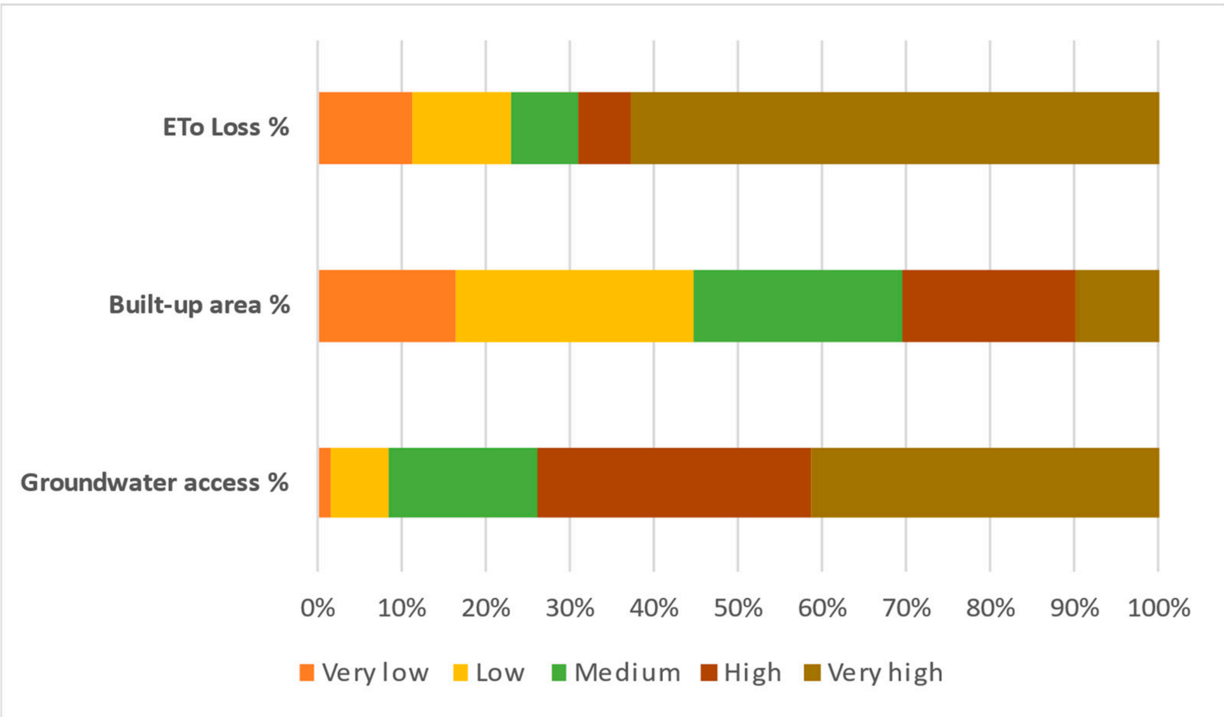

Figure 3. Percentage of grassed area ETo loss, surrounding built-up area intensity, and groundwater access across Greater Manchester for June 2018.

The built-up area vulnerability layer results indicate that 9.88% (approx. 20 km^2) of grass patches had very high built-up intensity within a 100 m radius around them, being situated within densely developed areas of GM (Figure 3). Furthermore, 45% of grass patches (approx. 93 Km^2) had high−medium built-up area intensity within a 100 m buffer zone. This indicates that GM's grassed areas are fragmented, with a large proportion surrounded by developed areas. This acts to increase the sensitivity of smaller fragmented grass patches to conditions of low water availability in comparison to larger areas of grass that are surrounded by less intensely built-up areas. This is potentially due to dense built-up areas hindering rainwater infiltration and ground water recharge [71,72], resulting in lower water availability for grass patches located in dense urban settings. Regarding groundwater access, the results highlight that more than 74% of GM's grassed areas had high or very high levels of access to groundwater, with water located between 10 and 30 m from the surface level (Figure 3). In these areas, adaptive capacity levels are therefore relatively high, with good accessibility to groundwater close to the surface level that could potentially be used to irrigate grass under conditions of low water availability.

Combining the hazard exposure and vulnerability layers, Figure 4 presents the final risk assessment result. According to this assessment, most of GM's grassed areas (around 61%, or 126 km^2) are at low or very low risk from low water availability conditions. Grass patches located around the periphery of GM, particularly to the north and east (characterized by upland moorland landscapes) and southwest (characterized by lowland agricultural landscapes) generally exhibited low or very low levels of risk. However, around 12% of grassed areas (approx. 25 km^2) are at high or very high risk from this hazard. These grassed areas, situated within densely urbanized and populated locations of GM, display high or very high ETo loss, high or very high built-up surroundings and low or very low potential to access groundwater for irrigation. These grassed areas therefore have high or very high levels of risk to low water availability, conditions that could become more commonplace in GM as a result of projected climate change.

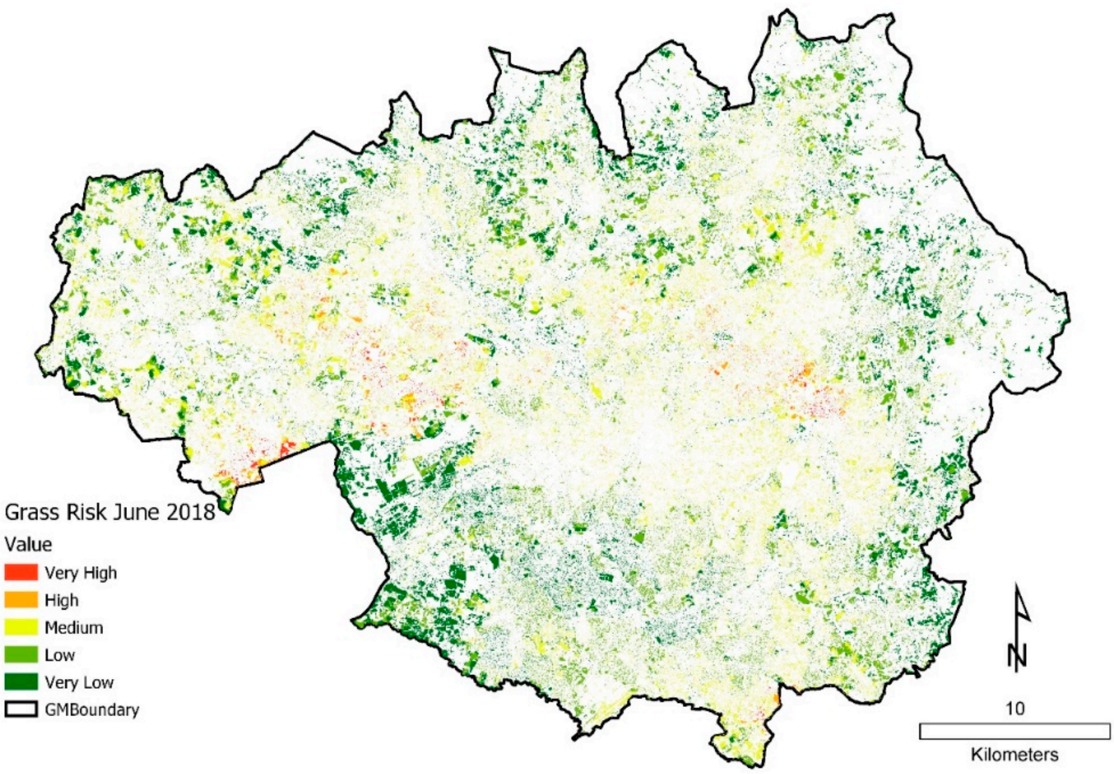

Figure 4. Risk to Greater Manchester's grassed areas from low water availability conditions in June 2018.

A considerable proportion of GM's grassed areas show a very high loss of potential ETo due to conditions of SWD and an associated lack of precipitation around June 2018 (Figures 2 and 3). However, most of these areas show low risk to conditions of low water availability (Figure 4). Although hazard exposure is very high, based on the indicators used to inform this risk assessment approach, sensitivity to harm is low and adaptive capacity to respond to this hazard is high. In aggregate, therefore, lower levels of vulnerability are acting to moderate levels of risk.

In this case study, higher levels of adaptive capacity are connected to a theme requiring proactive steps to be taken to realize risk reduction outcomes in practice; groundwater must be extracted and then utilized for irrigation purposes. Similarly, other recognized indicators of higher levels of capacity to adapt to climate change hazards, such as the presence of collaborative governance structures and the ability to forecast hazard events [73], necessitate tangible action to be taken to enhance adaptive capacity in practice. This differs from the sensitivity indicator incorporated within this risk assessment methodology, where high presence of built environment around grassed areas directly increases their susceptibility to harm from conditions of low water availability due to landscape fragmentation. Similarly, sensitivity of people to flooding and high temperatures in urban areas links to themes including age and health status, which directly makes certain people more susceptible to harm from these specific hazards [74,75]. It is not possible to account for whether groundwater was accessed to provide irrigation capacity action during the hazard event that GM's grassed areas were exposed to 2018. Consequently, if no active management took place to leverage this adaptive capacity opportunity, by accessing groundwater for irrigation, level of risks from low water availability would therefore be higher than presented in Figure 4.

When risk to GM's grassed areas from low water availability conditions was evaluated at the LSOA scale and analyzed alongside socio-economic deprivation levels at this scale, a significant difference in mean risk level between the most and least deprived areas was identified. As illustrated in Figure 5, grass patches located within LSOA areas with higher levels of deprivation usually have higher average risk values than grass patches located within less deprived areas. The one-way ANOVA results confirm a significant difference in risks to grass patches situated in the most versus the least deprived LSOA areas, $F(9, 1662) = 22.86$, $p = 0.000$ (Table 1). A further investigation of mean risk scores between different IMD deciles was performed using Tukey's HSD post-hoc analysis, with the result showing a significant difference in risk between different IMD deciles (see Appendix A, Table A2). Notably, immediate pairs of deprivation deciles (e.g., decile 1 vs. 2 or decile 9 vs. 10) often did not demonstrate significant differences in risk values. In contrast, the most significant difference was observed between risk values within the most deprived deciles (i.e., 1, 2, 3) vs. the least deprived deciles (i.e., 8, 9, 10). These results indicate that there is an unequal spatial distribution of GM's grassed areas at high risk from low water availability conditions between LSOAs displaying different level of socio-economic deprivation. During the period of low water availability that occurred during the summer of 2018, grassed areas located within highly deprived areas of GM were more likely to become dry leading to a reduction in their evapotranspiration functions, in comparison with grassed areas located in the least deprived areas of GM. These results are indicative of broader socio-economic inequalities concerning access to high functioning GI resources.

Table 1. One way ANOVA comparing the mean GI risk values between different neighbourhood with varying deprivation levels.

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	105.040	9	11.671	22.86	0.000
Within Groups	848.532	1662	0.511		
Total	953.571	1671			

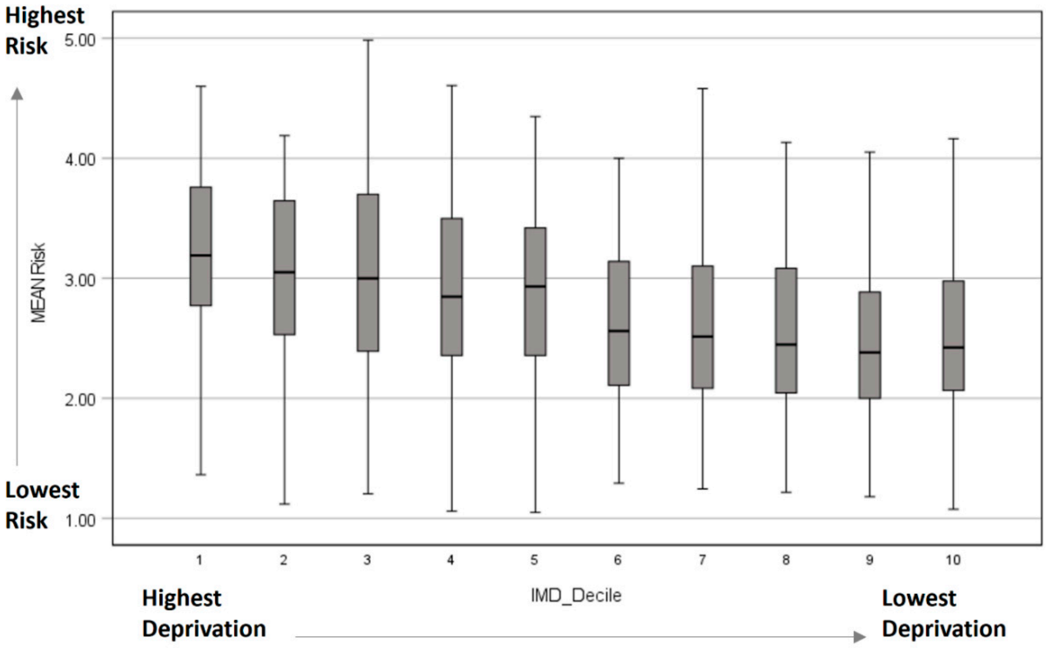

Figure 5. Average risk values for grass patches located in neighborhoods with varying socio-economic deprivation levels.

5. Discussion

Existing studies highlight how urban GI can be adapted to current extreme weather events, with particular attention paid to heat waves, e.g., [29,35]. Looking beyond the present day, adapting urban GI to extreme weather and climate change has received relatively limited attention. Although this topic remains under-researched [34,47], several studies have identified potential adaptation measures for different GI types, especially urban forests [47,76–78], but also including green roofs [79], stormwater management systems [80] and urban grasslands [30]. This paper links to this emerging literature and extends it into the field of risk and risk assessment. It represents a novel contribution focused on understanding and assessing risk to urban GI and identifying benefits that climate change risk assessment can offer to GI planning. Here, the value of assessing risk spatially is paramount. This can support the development of spatially targeted approaches, applying insights emerging from research on adaptation measures for reducing extreme weather and climate change risk to GI. In addition, spatially oriented risk assessment approaches can inform decisions around the prioritization of GI resources and capacities.

Crucially, the method followed within the GM case study identifies specific locations where risk to grassed areas from an extended period of low water availability, and therefore of associated ecosystem functionality being lost, is greatest. In the context of urban grasslands, functions linked to reducing flood risk, including rainwater capture by vegetation, increasing surface roughness to reduce flow rates into water courses, and provision of capacity for water to infiltrate into soils [55], are compromised as grasses die back. For example, exposed soils subsequently dry out more quickly, therefore reducing their permeability, particularly to intense short duration rainfall events [81,82]. In addition, under conditions of high or very high ETo loss, the evaporative cooling functionality of grassed areas is also reduced [69,70,83], which can lead to the loss of ecosystem services linked to moderating urban temperatures under heatwave conditions. Understanding where the risk of losing such ecosystem functions is greatest offers the opportunity to prioritize adaptation intervention towards these locations. Working in this way, risk assessments can encourage strategic and spatially informed GI planning approaches targeted at maintaining the provision of valuable ecosystem functions under extreme weather and climate change conditions.

This paper also demonstrates that the analytical power of outputs identifying patterns of climate change risk to GI can be enhanced through the exploration of spatial relationships to relevant GI planning themes. This was illustrated within the GM case study from the perspective of risk to grassed areas and levels of socio-economic deprivation. It is recognized that the presence of and access to grassed areas (and other GI forms, including trees and shrubs) can help to alleviate factors that characterize high levels of socio-economic deprivation, including poor health and social exclusion [84]. The identification of grassed areas at high risk from low water availability that coincide spatially with highly deprived neighborhoods presents GI planners with evidence to support the prioritization of such areas for GI conservation and enhancement, with the related goal of lessening deprivation outcomes. Additional spatial relationships could be explored to build the case for targeted GI interventions, including exploring connections between GI at high risk from extreme weather and climate change and surface water flooding hotspots, densely populated areas where there is limited accessible GI, and urban areas exposed to high summer temperatures.

Given the constraints on public realm and GI budgets in some locations [25,85], risk assessments that can inform decisions linked to focusing scarce resources on priority locations based on an understanding of levels of extreme weather and climate change risk to GI, and/or where risk intersects with areas of socio-economic or biophysical need for GI, are of potential value. Where funding constraints are less pressing, risk-based outputs can support more efficient and effective allocation of resources directed to the conservation, enhancement and expansion of GI sites, taking into consideration extreme weather and climate change risk factors. Acknowledging the potential longevity of urban GI, and the time it can take for GI interventions to reach maturity, are important considerations for GI planners. The fine scale nature of the GM risk assessment presented within this paper is beneficial from this perspective and distinguishes this study from the city scale assessment of climate change risk to urban forests developed by [47].

Beyond demonstrating the value of spatial assessments of extreme weather and climate change risk to GI planning, the second key contribution of this paper is to offer a replicable methodology for undertaking such risk assessments, with this paper representing the first application of the IPCC's current risk-based approach [38] in this context. In the GM case, risk to grassed areas from a period of low water availability involved accounting for SWD, rainfall patterns, soil conditions, landscape fragmentation and potential for groundwater access. Extensive data on these risk determinants, which will differ depending on the GI type being studied, was required to undertake this study and it is acknowledged that this factor may limit the implementation of similar approaches in data-poor contexts. Looking forward, further research would be valuable to progress the development of methods to assess extreme weather and climate change risk to urban GI to strengthen related outputs and enhance contributions to urban GI planning. In this study, we were unable to account for how different grass and tree species generate variability in risk assessment outcomes, and studies on the differences between GI types (e.g., grass, trees, shrubs) in this respect would therefore be valuable. However, such analyses would face challenges of their own linked to themes including obtaining data on the specific rooting depth and crop-coefficient values needed to model evapotranspiration loss for diverse vegetation types. In addition, detailed spatial information on the location of different GI types and species would be needed, which may again be difficult to access. A further limitation of the GM study reported within this paper concerned the omission of grass patches existing below the canopy of large trees, and investigation of this issue could enhance the risk assessment outputs. Looking beyond the vulnerability indicators utilized within this study, other urban morphology and climate variables, such as the urban heat island effect, have the potential to influence how certain GI types respond to low water availability conditions [86]. Incorporating the urban heat island effect into a GI-focused climate change risk assessment process would be a useful avenue for further research. Finally, within this study, the risk determinants were equally weighted in the risk calculation function. However, drawing on detailed local knowledge of vegetation types and urban conditions, each determinant could be weighted differently within further studies to reflect their relative importance in influencing the ecosystem functionality of specific GI types under investigation.

6. Conclusions

It is widely acknowledged that GI can support urban areas in adapting and becoming more resilient to climate change and associated extreme weather events, whilst realizing a wide range of additional multifunctional benefits. As a result, urban GI is now variously termed critical green infrastructure, essential infrastructure, and critical natural capital [4]. There has also been a growing economic conceptualization of GI resulting in debates extending beyond ecological themes, which is reflected in the increased prominence afforded to GI within policy structures and the wider recognition of its ability to generate multiple material socio-economic benefits [87]. In turn, GI is now linked to arguments around the competitiveness of cities and urban areas [88,89].

Although GI is increasingly being positioned as an asset for urban areas, it is also understood that GI is constrained by various political, economic, legislative, and technical factors that act to compromise the realization of the multifunctional benefits that GI has the potential to offer. This paper emphasizes that, in addition to these constraints, extreme weather and climate change can pose a significant risk to urban GI, further threatening its functionality, including from the perspective of supporting urban climate change adaptation. Understanding and assessing climate change risk provides a foundation for climate change adaptation, as exemplified by the IPCC's risk-based conceptual framework, and it follows that efforts to increase the climate resilience of urban GI can be informed by risk-based approaches.

However, at present, climate change risk assessment research and practice is lacking in the urban GI field, which is holding back the realization of benefits that can stem from developing such risk-based knowledge. The GM case study outlined in this paper, which implements a transferable risk assessment methodology, identifies that these benefits link to themes including analyzing risk patterns and determinants and utilizing these insights to inform urban GI planning and action. This paper therefore takes a step towards incorporating risk-based approaches within the process of planning for and responding to extreme weather and climate change within urban GI research and practice. It clarifies that extreme weather and climate change risk to GI is a spatial phenomenon, and that risk assessment methods can reduce the spatial complexity of related risks by offering new visual perspectives. Building on these insights, expanding the assessment of extreme weather and climate change risks can support the transition towards climate-resilient urban GI sites and networks that are able to sustain the provision of multifunctional benefits under future climate change conditions.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Soil type related RZAWC and LIMDEF.

SERIES_NAME	Series Number	RZAWC (in mm)	LIMDEF (in mm)
ALUN	37	117.75	78.65
BELMONT	113	109	71.8
BLACKWOOD	124	119.35	97.25
BRICKFIELD	142	90.5	51.9
CONWAY	236	101.9	60.9
CRANNYMOOR	242	87.45	63.6
CREWE	244	81.25	46.75
ENBORNE	413	111.95	70.25
FLINT	514	98.2	60.7
LONGMOSS	1136	253.3	219.5
NEWPORT	1310	83.75	62.5
RIVINGTON	1713	113.7	73.2
RUFFORD	1726	92.5	56.4
SALOP	1802	95.9	61.15
SOLLOM	1833	81.4	62.45
TURBARY MOOR	1928	252.5	212.5
WICK	2225	123.8	85.5
WILCOCKS	2235	145.5	100
WINTER HILL	2242	267.4	236.5

Table A2. ANOVA post-hoc analysis using Tukey HSD method.

Multiple Comparisons						
Dependent Variable: MEAN GI Risk						
Tukey HSD						
(I) IMD_Decile	(J) IMD_Decile	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	0.113	0.060	0.693	−0.079	0.304
	3	0.149	0.065	0.385	−0.056	0.353
	4	0.315 *	0.067	0.000	0.104	0.526
	5	0.298 *	0.074	0.003	0.062	0.533
	6	0.548 *	0.074	0.000	0.314	0.783
	7	0.553 *	0.081	0.000	0.297	0.809
	8	0.589 *	0.071	0.000	0.365	0.813
	9	0.714 *	0.073	0.000	0.482	0.946
	10	0.651 *	0.080	0.000	0.396	0.906

Table A2. *Cont.*

Multiple Comparisons						
Dependent Variable: MEAN GI Risk						
Tukey HSD						
(I) IMD_Decile	(J) IMD_Decile	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
2	1	−0.113	0.060	0.693	−0.304	0.079
	3	0.036	0.070	1.000	−0.185	0.258
	4	0.202	0.072	0.133	−0.026	0.430
	5	0.185	0.079	0.363	−0.065	0.435
	6	0.436 *	0.079	0.000	0.186	0.685
	7	0.441 *	0.085	0.000	0.171	0.710
	8	0.476 *	0.076	0.000	0.236	0.716
	9	0.601 *	0.078	0.000	0.354	0.848
	10	0.538 *	0.085	0.000	0.269	0.807
3	1	−0.149	0.065	0.385	−0.353	0.056
	2	−0.036	0.070	1.000	−0.258	0.185
	4	0.166	0.075	0.455	−0.073	0.405
	5	0.149	0.082	0.728	−0.112	0.409
	6	0.399 *	0.082	0.000	0.140	0.659
	7	0.404 *	0.088	0.000	0.125	0.683
	8	0.440 *	0.079	0.000	0.190	0.690
	9	0.565 *	0.081	0.000	0.308	0.822
	10	0.502 *	0.088	0.000	0.224	0.780
4	1	−0.315 *	0.067	0.000	−0.526	−0.104
	2	−0.202	0.072	0.133	−0.430	0.026
	3	−0.166	0.075	0.455	−0.405	0.073
	5	−0.017	0.084	1.000	−0.283	0.248
	6	0.233	0.084	0.142	−0.032	0.498
	7	0.238	0.090	0.192	−0.046	0.522
	8	0.274 *	0.081	0.025	0.018	0.530
	9	0.399 *	0.083	0.000	0.136	0.662
	10	0.336 *	0.089	0.007	0.052	0.619
5	1	−0.298 *	0.074	0.003	−0.533	−0.062
	2	−0.185	0.079	0.363	−0.435	0.065
	3	−0.149	0.082	0.728	−0.409	0.112
	4	0.017	0.084	1.000	−0.248	0.283
	6	0.251	0.090	0.141	−0.034	0.535
	7	0.256	0.095	0.183	−0.047	0.558
	8	0.291 *	0.087	0.029	0.015	0.567
	9	0.416 *	0.089	0.000	0.134	0.699
	10	0.353 *	0.095	0.008	0.051	0.654

Table A2. *Cont.*

Multiple Comparisons						
Dependent Variable: MEAN GI Risk						
Tukey HSD						
(I) IMD_Decile	(J) IMD_Decile	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
6	1	−0.548 *	0.074	0.000	−0.783	−0.314
	2	−0.436 *	0.079	0.000	−0.685	−0.186
	3	−0.399 *	0.082	0.000	−0.659	−0.140
	4	−0.233	0.084	0.142	−0.498	0.032
	5	−0.251	0.090	0.141	−0.535	0.034
	7	0.005	0.095	1.000	−0.297	0.307
	8	0.041	0.087	1.000	−0.235	0.316
	9	0.166	0.089	0.695	−0.116	0.448
	10	0.102	0.095	0.987	−0.199	0.403
7	1	−0.553 *	0.081	0.000	−0.809	−0.297
	2	−0.441 *	0.085	0.000	−0.710	−0.171
	3	−0.404 *	0.088	0.000	−0.683	−0.125
	4	−0.238	0.090	0.192	−0.522	0.046
	5	−0.256	0.095	0.183	−0.558	0.047
	6	−0.005	0.095	1.000	−0.307	0.297
	8	0.036	0.093	1.000	−0.258	0.329
	9	0.161	0.095	0.797	−0.139	0.460
	10	0.097	0.100	0.994	−0.220	0.415
8	1	−0.589 *	0.071	0.000	−0.813	−0.365
	2	−0.476 *	0.076	0.000	−0.716	−0.236
	3	−0.440 *	0.079	0.000	−0.690	−0.190
	4	−0.274 *	0.081	0.025	−0.530	−0.018
	5	−0.291 *	0.087	0.029	−0.567	−0.015
	6	−0.041	0.087	1.000	−0.316	0.235
	7	−0.036	0.093	1.000	−0.329	0.258
	9	0.125	0.086	0.911	−0.148	0.398
	10	0.062	0.092	1.000	−0.231	0.355
9	1	−0.714 *	0.073	0.000	−0.946	−0.482
	2	−0.601 *	0.078	0.000	−0.848	−0.354
	3	−0.565 *	0.081	0.000	−0.822	−0.308
	4	−0.399 *	0.083	0.000	−0.662	−0.136
	5	−0.416 *	0.089	0.000	−0.699	−0.134
	6	−0.166	0.089	0.695	−0.448	0.116
	7	−0.161	0.095	0.797	−0.460	0.139
	8	−0.125	0.086	0.911	−0.398	0.148
	10	−0.063	0.094	1.000	−0.362	0.236

Table A2. *Cont.*

Multiple Comparisons						
Dependent Variable: MEAN GI Risk						
Tukey HSD						
(I) IMD_Decile	(J) IMD_Decile	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
10	1	−0.651 *	0.080	0.000	−0.906	−0.396
	2	−0.538 *	0.085	0.000	−0.807	−0.269
	3	−0.502 *	0.088	0.000	−0.780	−0.224
	4	−0.336 *	0.089	0.007	−0.619	−0.052
	5	−0.353 *	0.095	0.008	−0.654	−0.051
	6	−0.102	0.095	0.987	−0.403	0.199
	7	−0.097	0.100	0.994	−0.415	0.220
	8	−0.062	0.092	1.000	−0.355	0.231
	9	0.063	0.094	1.000	−0.236	0.362

*. The mean difference is significant at the 0.05 level.

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