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REVIEW ARTICLE

An urban drought categorization framework and the vulnerability of a lowland city to groundwater urban droughts

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Abstract
Due to climate change, droughts will intensify in large parts of the world. Drought and its impacts on nature and agriculture have been studied thoroughly, but its effects on the urban environment is rather unexplored. But also the built environment is susceptible to droughts and estimation of its vulnerability is the first step to its protection. This article is focusing on assessing the vulnerability of a city to groundwater drought, using parts of the lowland city of Leiden, the Netherlands, as a case study. Using a new urban drought categorization framework, groundwater drought is separated from soil moisture drought, open water drought and water supply drought, as each has its own impacts. Vulnerability was estimated as the aggregation of drought exposure and damage sensitivity. Drought deficit and duration were used as exposure indicators. Both a Fixed and Variable threshold method was used to quantify these indicators. To quantify drought vulnerability weights were assessed for selected exposure and damage sensitivity indicators using an Analytical Hierarchy Process (AHP) with a small number of experts. Based on these weights the spatial variation in vulnerability for groundwater drought follows damage sensitivity patterns—rather than exposure ones. And, out of all damage sensitivity indicators used, 'land use', 'low income' and 'monuments' contributed the most to the spatial variation in vulnerability. Due to the fact that the number of drought experts' opinions in the AHP was limited these vulnerability results however remain uncertain. The proposed methodology however allows water managers to determine vulnerability of urbanized areas to groundwater drought, identify highly vulnerable areas and focus their mitigating actions.

Keywords Drought · Vulnerability · Urban areas · Groundwater drought · Damage sensitivity · Exposure

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1 Introduction

The consequences of droughts are devastating, not only for the rural environment.[1] Drought is also an increasing problem for the built environment. With an ongoing urbanization—about 66% of the global population is predicted to live in cities by 2050 (United Nations 2014)—and ongoing climate change (IPCC 2021) the vulnerability of cities to droughts will certainly increase (Güneralp et al. 2015). In cases of global warming at 1.5 °C and 2 °C above the preindustrial levels, the global urban population exposed to droughts will increase by 350.2 and 410.7 million residents, respectively (Liu et al. 2018). Yet, surprisingly, the impact of drought on the built environment has not been studied intensively (Yuan et al. 2015; Chang et al. 2015; Zhang et al. 2019; Dong et al. 2020; Wang et al. 2020), despite the fact that many assets and interests are clustered there. In general, there is an annual increase (12.7%) of publications regarding droughts over the past years (Orimoloye et al. 2021) which highlights the importance of this phenomenon.

Many problems can be created by droughts in urban environment. During drought periods of extreme drought, employee's productivity decreases, salaries are reduced and unemployment increases (Desbureaux and Rodella 2019; Chen and Chan 2007). The spreading of contagious diseases is larger during droughts (Kovats et al. 2003). Furthermore, droughts decrease the groundwater level and subsidence may occur in soft soil lowland areas causing damage not only to buildings but also to roads, subsurface infrastructure and flood protection (Van de Ven et al. 2011). A major problem in the Netherlands is however is the deterioration of wooden pile foundations under historic buildings. Part of their cultural heritage is seriously at risk.

Wilting of the vegetation in urban parks due to low soil moisture is another adverse impact of drought but damage strongly depends on the species (Van de Ven et al. 2011). The reduced evaporation leads to higher temperatures, enhancing the urban heat island effect. The hazard of wildfires increases and firefighting could cause serious problems with the water supply network (Knutson et al. 1998). Drought also leads to water quality degradation in the urban canals and waterways, due to stagnation, eutrophication and survival of pathogenic organisms. And, last but not least, lack of drinking water is another consequence; Cape Town faced a serious water crisis due to a drought in 2015–2017.

Droughts can be categorized into meteorological, agricultural, hydrological, and socioeconomic ones (Wilhite and Glantz 1985). The diversity of impacts however makes a universal definition impossible since (i) so many other components besides precipitation play a role to a water system that is short of water, and (ii) different stakeholders are impacted under different circumstances which are impossible to cover in one all-inclusive definition (Lloyd-Hughes 2014; Heim Jr 2002). The simplest definition has been given by Sheffield and Wood (2012) [p.11] which is "a deficit of water relative to normal conditions". The inability of providing a clear definition for droughts leads to ineffective research about this phenomenon (Yevjevich 1967). This certainly holds true for drought in the complex urban system.

Urban drought can be considered as a type of socioeconomic drought (Zhang et al. 2019), but Rossi et al. (1992) considered it to be a distinct category. Zhang et al. (2019) classified urban droughts into precipitation-induced, runoff-induced, pollution-induced,

[1] Damage sensitivity to damage is often referred to as vulnerability. But Vulnerability is defined in literature in many different ways. That is why the term 'damage sensitivity' is used in this article.

and demand-induced but a method is missing to test which type of drought a city faces and which actions to take. Thus, there is a need for a comprehensive, operationalizable framework for urban drought analysis.

The main goals of this paper are: (i) to create a framework for analyzing the urban drought, based on which policy makers of a city can classify the drought from an action perspective and (ii) to operationalize the analysis of one of the elements of this framework, i.e., groundwater drought, and turn it into a method to quantify the groundwater drought vulnerability of an urban area. A case study in the lowland city of Leiden, the Netherlands, will be used to elaborate and demonstrate this method.

2 Methodology

2.1 Frameworks for drought vulnerability assessment

A general framework for assessing climate resilience–and, hence, for drought resilience—is the vulnerability framework. According to the Intergovernmental Panel on Climate Change (IPCC 2007) [p. 27] "Vulnerability is the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes". In order to assess vulnerability, there is a host of available vulnerability frameworks, each with its advantages and disadvantages. (e.g., Turner et al. 2003; Bohle et al. 1994; Birkmann et al. 2013; Hoque et al. 2020). On top of that many vulnerability assessment techniques have been proposed by scholars; Regmi et al. (2010); Hossain and Roy (2012) used a qualitative method (community risk assessment) whereas Alcamo et al. (2005) used fuzzy set theory to weight model factors and convert qualitative variables to quantitative indicators. Data-driven techniques have also been applied; da Silva et al. (2021); Sharma and Patwardhan (2008) used cluster analysis and Li et al. (2021) random decision trees.

King et al. (2020) grouped the drought vulnerability methods used in eight developing countries (Brazil, Mexico, Colombia, India, Slovenia, Nigeria, Senegal and Kenya) into three overlapping categories: land-based, people-centered, and water-balanced paying attention to the most vulnerable communities. Fritzsche et al. (2014) created frameworks with exposure, damage sensitivity, and adaptive capacity as its main components, in-line with their definitions in IPCC (2007), providing the basis for a risk-based approach to drought resilience.

Drought vulnerability of cities was studied particularly in China. Dong et al. (2020) used a quantitative indicator-based vulnerability assessment of urban water infrastructures to floods and droughts in 22 of provincial capital cities in China. Thirty-three indicators were considered and categorized into exposure, damage sensitivity and adaptive capacity ones. For the latter two categories, indicators were clustered into the following dimensions: physical, social, economic, and environmental. The indicators weights were assigned as equal except the physical dimension which was larger for both damage sensitivity and adaptive capacity. Chang et al. (2015) investigated the vulnerability of seven cities in China located on the northern slope of Tianshan Mountain. Wang et al. (2020) assessed the vulnerability of Beijing-Tianjin-Hebei (BTH) region which is formed by two municipalities, Beijing and Tianjin, and 11 cities of Hebei Province. In both studies, they used a variety of data regarding economy, society, ecology, and social resources and employed the entropy method (Iyengar and Sudarshan 1982) for estimating of their weights in the evaluation.

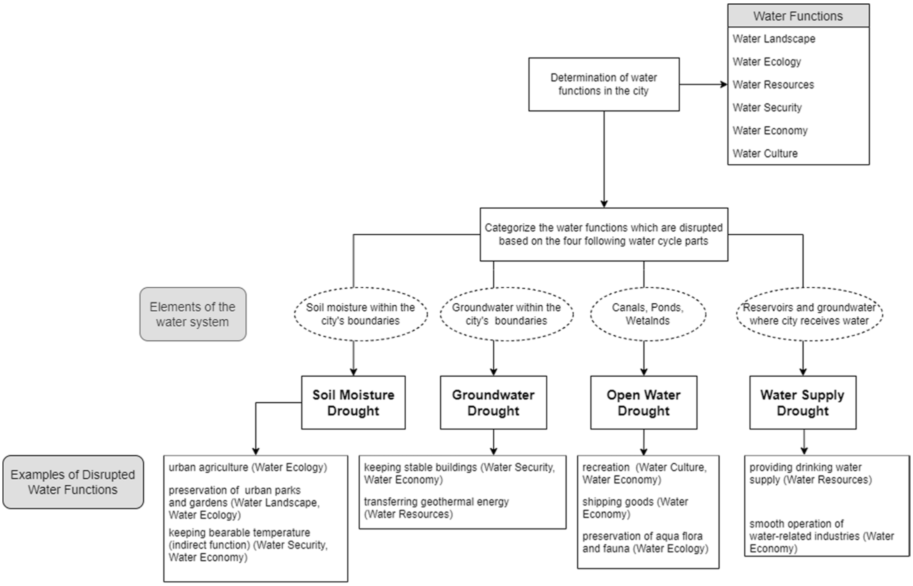

Fig. 1 Urban Drought Categorization Framework; four types of urban drought, related to their element of the water system and their impact on the urban system

Yuan et al. (2015) also studied the drought vulnerability of 65 cities in China, using variables based on exposure, damage sensitivity, and adaptive capacity. These authors estimated the weights using an Analytical Hierarchy Process (AHP) (Saaty 1980). Another study worthwhile mentioning is by Corti et al. (2009, 2011). They investigated the damage of buildings due to subsidence and created vulnerability curves which converted the soil moisture deficit to monetary damage.

2.2 Urban drought categorization framework

Urban drought is to be defined in the context of drought vulnerability. To that end we state: Urban drought occurs when at least one of the water-dependent urban functions and services is 'disrupted' due to the fact that a specific element of the urban water system–surface water, groundwater, soil moisture in the unsaturated zone, supplied water—has less water than the minimal expected, in terms of quantity and/or quality. The term 'disrupted' means there is a deviation for a water function from normal conditions to such a degree that the city starts facing losses regarding society, economy, and/or environment. Hence, urban droughts are region and climate dependent, since an urban drought in one city influences other water-dependent urban functions than in another city and since the minimal expected quantity /quality in an arid zone is different from an area with a wet sea climate.

A solid urban drought classification system can be made by linking the water-dependent urban functions and services to the specific elements of the urban water system (see Fig. 1). To operationalize this classification, policy makers need to spatially define the water-dependent urban functions and services in their city, as these determine the (damage) sensitivity of being exposed to drought. Areas–including surface waters—can have multiple water-dependent functions and provide multiple services. Water-dependent urban functions can be categorized into the following classes: water landscape, water ecology, water resources, water security, water economy, and water culture (Yu et al. 2018).

The degree to which drought has an impact on an urban environment is quantified by the drought risk, that is the product of exposure to drought–including its frequency of exposure and intensity—and the (damage) sensitivity of the urban system. The hazard of being exposed to drought is to be assessed from the perspective of the specific elements of the urban water system that support these functions and services. The four relevant specific elements are local soil moisture, local groundwater, local surface water (canals\ponds\wetlands), and surface water and groundwater reservoirs from which the city receives its drinking and industrial water. These reservoirs are generally located beyond the boundaries of the built environment. According to the four affected elements of the water system, we can differentiate between four urban drought categories: Soil Moisture Drought (SMD), Groundwater Drought (GD), Open Water Drought (OWD), and Water Supply Drought (WSD). These four types of drought can be the result of a shortage of water (quantity), but also due to poor quality, so that the water can no longer be used for the functions it is supposed to serve. It is very well possible that in a specific area more than one of these urban drought types occur simultaneously.

Some examples of disrupted water functions are provided so that the framework becomes more tangible and easier to be applied. SMD will damage urban parks and urban agriculture and will increase ambient air temperatures due to the reduction of evapotranspiration. GD can lead to land subsidence and damage to buildings due to foundation problems due to shrinking clay layers in the subsurface. Wooden pole foundations of (historic) buildings are in particular sensitive to low groundwater levels, as they start rotting when exposed to air in an unsaturated zone. OWD leads to damage in lowland and delta cities with their canals, ponds and wetlands, as surface water functions such as recreation, shipping goods, and preservation of aqua flora and fauna are restricted by a lack of sufficient water of sufficient quality. Last but not least, the urban drought category which has the most significant impact on a city is WSD. Providing clean and sufficient water to its residents and for a smooth operation of water-dependent industries is essential for the continuity of the urban society.

Though their impacts are different, the different types of urban droughts are interrelated. SMD can cause GD since less percolation occurs due to lower soil moisture. In addition, GD can cause SMD, as less capillary rise takes place. A GD can cause an OWD in case there are canals or a pond in a city. Lower groundwater levels result in less water flows into the canals or pond, leading to an OWD. Additionally, GD can cause a WSD in case the supply comes from groundwater within a city's boundaries.

Next step in the operationalization of this framework is to find out which characteristics are required for quantifying the exposure to each specific urban drought and the area's damage sensitivity. This search for the relevant drought characteristics will be addressed in the case study.

2.3 Study area

The selected study area for this study was Leiden in the Netherlands for the two following reasons: (i) the city is well monitored, and (ii) it may face drought challenges in the future. Four pilot districts were focused on, to allow for a higher resolution vulnerability analysis: Binnenstad-Zuid, Binnenstad-Noord, Bos en Gasthuis, and Boerhaave (Fig. 2). These districts were

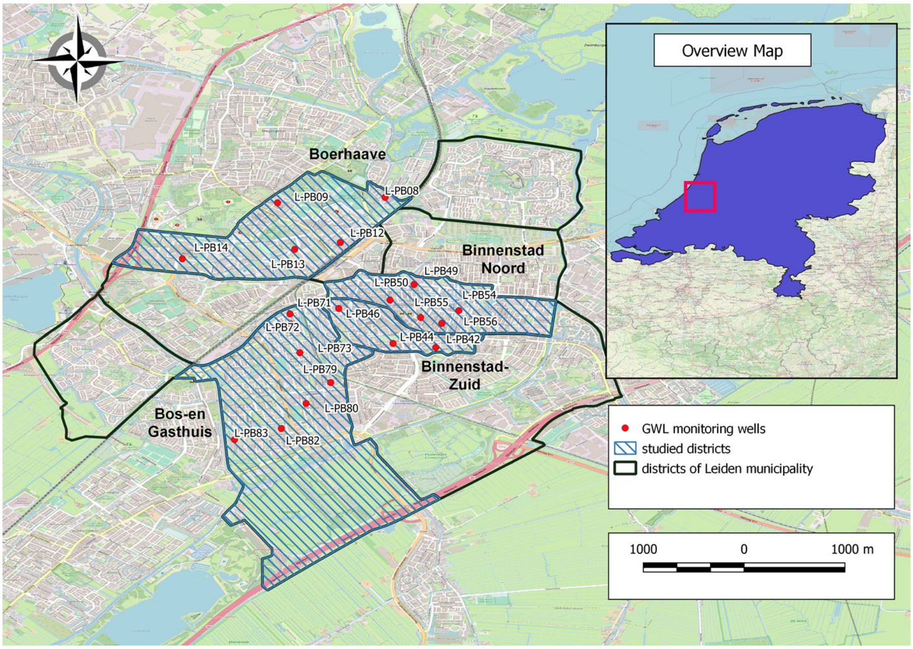

Fig. 2 Study area in Leiden and the positions of groundwater monitoring wells in these districts

selected because they were built in different periods and their soil type is different. In districts Binnenstad-Zuid, Binnenstad-Noord the main geological type is 'trench/trench deposits' whereas 'tidal basin/tidal deposits' dominates in Boerhaave. At district level there is homogeneity regrading hydrological conditions.

Our analysis will focus on GD; OWD is not relevant for this area, as all open water is connected to the regional system and is kept at a fixed level, even under extremely dry conditions. Drinking water is supplied from rich external sources, making WSD irrelevant as well. And SMD is less relevant to our case as the groundwater levels are normally around or even above 1 m below surface and during extreme droughts hardly ever more than 1.5 m below surface. Consequently, the unsaturated zone of these silty soils remains relatively wet and continues to provide water to the urban green even under conditions of drought. Groundwater levels however are important to minimize land subsidence, to keep buildings (foundations) stable and preserve wooden pile foundations.

Groundwater level observations were available for the hydrological year April 2018–March 2019. The summer of 2018 was extremely dry all over the country. Three wells were selected in Binnenstad-Zuid, five ones in Binnenstad-Noord, seven ones in Bos- en Gasthuis, and five ones in Boerhaave.

Raw groundwater level data was collected on an hourly basis but was resampled to daily averages as tiny groundwater fluctuations within 24 h are irrelevant for our analysis. Regarding missing values, linear interpolation was applied (see the overview of data gaps in Appendix).

2.4 Assessing exposure: threshold methods

To quantify exposure to groundwater droughts, groundwater level deficit and duration were determined, including their cumulative probability distribution and percentile values. Two different methods were compared for their ability to express and quantify GD exposure: (i) Fixed threshold, (ii) Variable threshold, i.e., using moving average of monthly quantile values as threshold (Beyene et al. 2014).

A Fixed threshold is a constant value groundwater level, based on a groundwater level percentile (e.g., the 30th percentile) considering the whole time series. Regarding the Variable threshold method, the following steps (see Fig. 3) were applied: (i) for each month of the year, the 30th percentile was determined using the cumulative distribution function (CDF) from all daily values in that month (ii) the value of the 30th percentile was assigned to all days of that month, and (iii) backwards moving average of 20 days was applied to the whole year to smooth the 'staircase differences' and extinguish the abrupt jumps in threshold function between consecutive months. For both threshold methods the study period was one year making sure that there are no inconsistencies in their comparison.

On beforehand, there is no reason to prefer a specific percentile as threshold value for assessing exposure. To investigate the differences, three percentiles (20th, 30th, and 40th) were applied for each of the three aforementioned techniques and their results were evaluated. The most common percentiles in the literature are 10th, 20th, and 30th (e.g., studies of Heudorfer and Stahl (2017) and Hisdal and Tallaksen (2000)). Tallaksen et al. (2009) have used only 20th percentile, whereas Gurwin (2014) has employed percentiles based on the standard deviation (50% of standard deviation). In the current study, given the range of groundwater data in study area and after testing a threshold of the 10th, 20th, 30th and 40th percentile, it was decided to use the 30th percentile. A percentile as low as 10 or 20% would lead to a very limited number of drought events, impeding further analysis.

Regarding groundwater level related drought indicators, *deficit* is defined as the maximum difference from the threshold during the drought event (Peters 2003; Van Loon and Van Lanen, 2012), as shown in Fig. 4. A drought event starts when the level is lower than the threshold and ends when it is higher again. Their difference defines drought *duration*. In Fig. 4, a Fixed threshold was used, but the same definitions for drought duration and deficit hold for Variable threshold method.

2.5 Assessing damage sensitivity; physical and social indicators

Damage sensitivity was split up into physical and social sensitivity.

2.5.1 Physical damage sensitivity indicators

Physical damage sensitivity indicators include physical attributes of the city which may be damaged by groundwater drought. Their malfunctioning can create serious disruption to the city. Seven variables were used to quantify this physical damage sensitivity: 'public buildings'; 'shops'; 'ontwatering'; 'buildings before 1960'; 'monuments'; 'land use'; and 'soil'. Data on 'shops', 'monuments', and public buildings' were derived from openstreetmap.org.

'shops' are related to the economic state of the district whereas 'monuments' to its cultural identity. Any disruption of these could lead to severe economic damages. 'public buildings' were considered as a critical part of the city and any malfunction of them, e.g.,

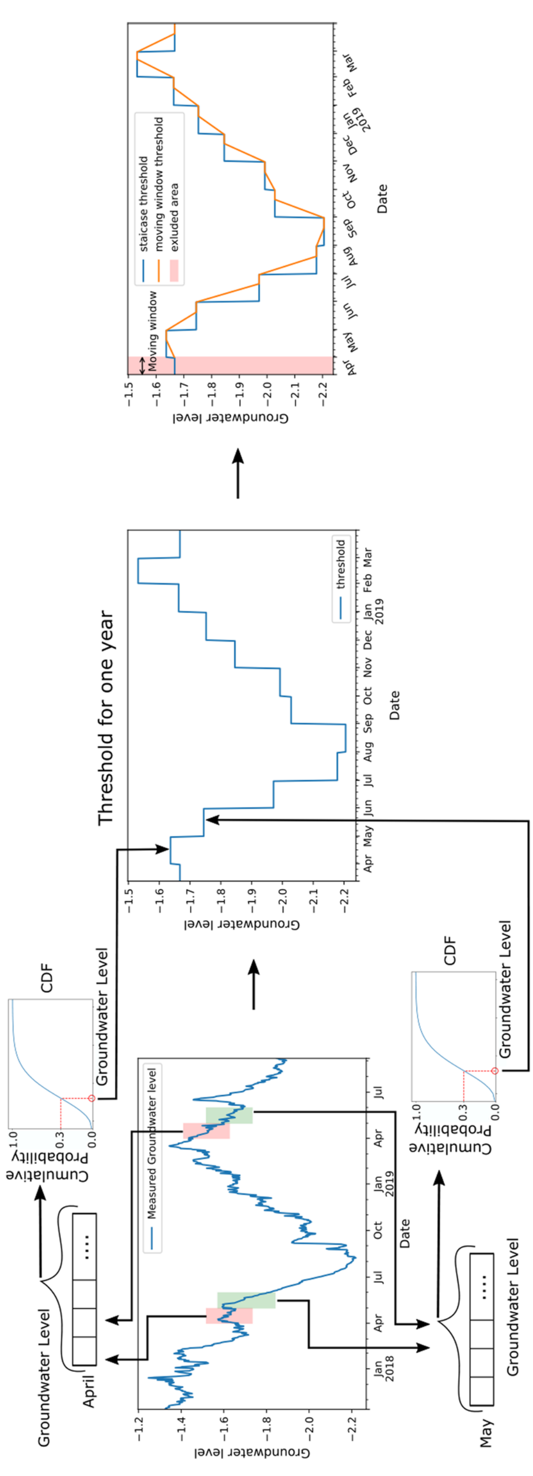

Fig. 3 Procedure of the Variable threshold method

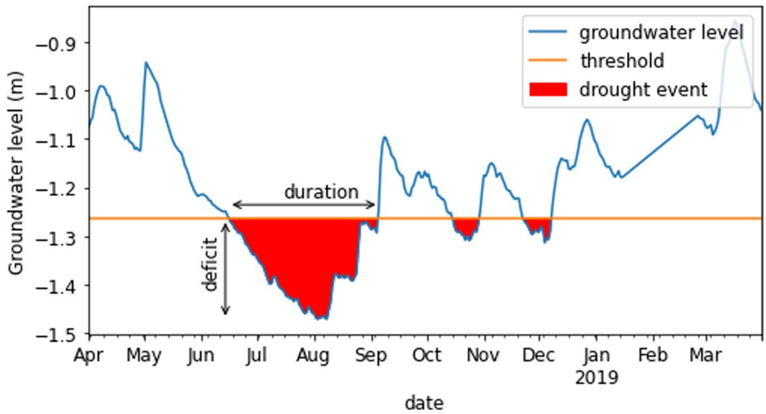

Fig. 4 Illustration of basic drought indicating variables Deficit and Duration using a Fixed threshold method for well L-PB56. Groundwater level in meters—Amsterdam Ordnance Datum. Ground level at this place is 0.415 m—AOD

due to subsidence, could create disruption. This indicator was also used to determine flood vulnerability of South-Western Ontario, Canada (Karmakar et al. 2010).

‘ontwatering’ was estimated as the difference of the lowest observed groundwater level and the ground surface. The larger the ‘ontwatering’, the more sensitive the area is for drought damage to vegetation, land subsidence and rot of wooden pile foundations under historic buildings. The lowest groundwater level was selected for each monitoring well for the period April 2018–March 2019 and then these values were interpolated via Inverse Weighted Interpolation (IWI) algorithm to cover the entire study area. Ground level data was derived from the Actueel Hoogtebestand Nederland (AHN2), the digital elevation map of the Netherlands with a spatial resolution of 0.5 m. Related to ‘ontwatering’, annual groundwater drop was used by Alamdarloo et al. (2020) to determine drought vulnerability.

Due to the soft soil and subsurface, most buildings in Leiden are built on poles. Since around 1960 concrete poles are used. But ’buildings before 1960’ are considered to be built on wooden poles. And these will degrade when no longer immersed in—almost anaerobic—groundwater, with fatal effects for the stability of the building. This data came from a municipal database. Indicators such as building age were also used to determine vulnerability to floods (Rana and Routray, 2016, 2018; Jamshed et al. 2020) but are relevant to groundwater drought analysis too.

‘soil’ and ‘land use’ are two characteristics which determine how destructive fast subsidence will be. Soil type affects its potential of compaction due to subsidence; peat and some clays are highly sensitive. And ‘land use’ is an indicator for buildings and infrastructure. The larger the subsidence, the higher the damage sensitivity of intensively developed areas. They are both derived from a municipal database. Henrique et al. (2021) and Alamdarloo et al. (2020) used ‘land use’ to identify vulnerable regions of Sao Paulo and Iran to droughts. ’land use’, and soil texture and depth were also used by Dayal et al. (2018) in the drought-prone region of south-east Queensland, Australia.

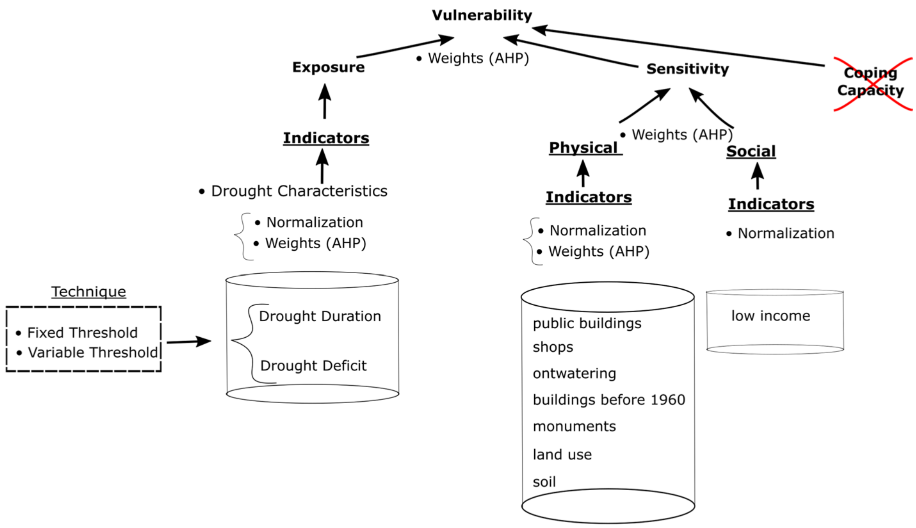

Fig. 5 Overview of the vulnerability assessment method for groundwater droughts for the Leiden case study

2.5.2 Social damage sensitivity indicators

Social indicators for groundwater droughts showcase minorities which may face hardships when a groundwater drought occurs. A variety of variables was available, including population, economy, and social security data. All social indicators data were collected at neighborhood level (Centraal Bureau voor de Statistiek 2017). Many variables proved to be highly correlated, as shown by their Kendall Tau coefficient; hence, they were rejected as being redundant. The percentage of households belonging to the lowest 40% income nationwide was selected as the most relevant social sensitivity indicator. From here onwards, it is named as 'low income'. Economic indicators regarding household income or per capita were used in previous studies by Abbas and Routray (2014); Rana and Routray (2016, 2018); Jamshed et al. (2020); Li et al. (2021) to determine vulnerability to floods but also to droughts (Henrique et al. 2021).

2.6 Vulnerability estimation

To determine vulnerability to groundwater droughts, the framework suggested by Fritzsche et al. (2014) was followed, though with some modifications. Changes were: (i) AHP was used to assign weights, (ii) coping capacity (called adaptive capacity by Fritzsche et al. (2014)) was not considered, as this component is equal in all districts. As all districts of the study area belong to the same municipality and are located close to each other, exposure and damage sensitivity were similar but not equal in all districts and are therefore relevant to the vulnerability estimation. Figure 5 illustrates the main concepts of this framework and the indicators we included. Vulnerability aggregation was applied via GIS overlay. The cell size used for vulnerability estimation was 23 m × 23 m.

2.7 Normalization

The indicators used in this study include metric and categorical ones. Categorical indicators can be categorized into two categories; ordinal and nominal ones. The former are ranked classes whereas the latter are descriptive ones. In the current analysis, there are two nominal indicators ('land use' and 'soil'); all other exposure and damage sensitivity indicators are metric. The min–max method is used for metric indicators' normalization; maximum vulnerability is represented by one and lowest vulnerability by zero.

For normalizing nominal indicators these are first converted to ordinal classes and then normalized to a range between zero and one. For example, 'soil' is a nominal indicator and was transformed to an ordinal one; peat soil was classified as 'rather negative', clay deposits as 'negative', and old dunes (consisted of loamy sand) as 'positive' regarding groundwater urban droughts. Then, values in the range [0–1] were assigned based on the classes. More information on the normalization of the nominal indicators can be found in Appendix.

2.8 Weights assessment

The Analytical Hierarchy Process (AHP; Saaty 1987) was used for assigning weights to vulnerability indicators and to aggregated components. Entropy evaluation and Garrett ranking were not feasible due to the very limited number of districts (spatial units) and available expert respondents. Eight drought experts, who worked either in public or private sector, compared indicators or vulnerability components in pairs for the AHP. For each expert, a comparison matrix was created and based on all experts' matrices, a combined one was developed to assess the weights of the indicators.

The robustness of weights' estimation was evaluated via their consistency ratio (see Supplementary material) which is a metric AHP uses to check the consistency of the experts' judgment (Saaty 1987). The next step is checking whether the consistency ratio exceeds the threshold of 0.1. AHP allows only 10% inconsistency for experts' judgment. Exceedance of this threshold means that the pairwise judgments are random and the weights are not reliable.

2.9 Vulnerability aggregation

After normalizing the indicators of exposure and damage sensitivity, aggregation was applied by weighted multiplication of all indicators and mapping the results. The vector type of most indicators (i.e., 'duration', 'deficit', 'buildings before 1960', 'monuments', 'public buildings', and 'shops') is point. Raster interpolation was applied for them so that the entire area has values regarding these indicators. The vector type of the remaining indicators ('soil', 'land use', 'ontwatering', and 'low income') is polygon but they are converted to raster so that raster multiplication can be performed. Next, the aggregated components were combined to determine the vulnerability map for groundwater drought.

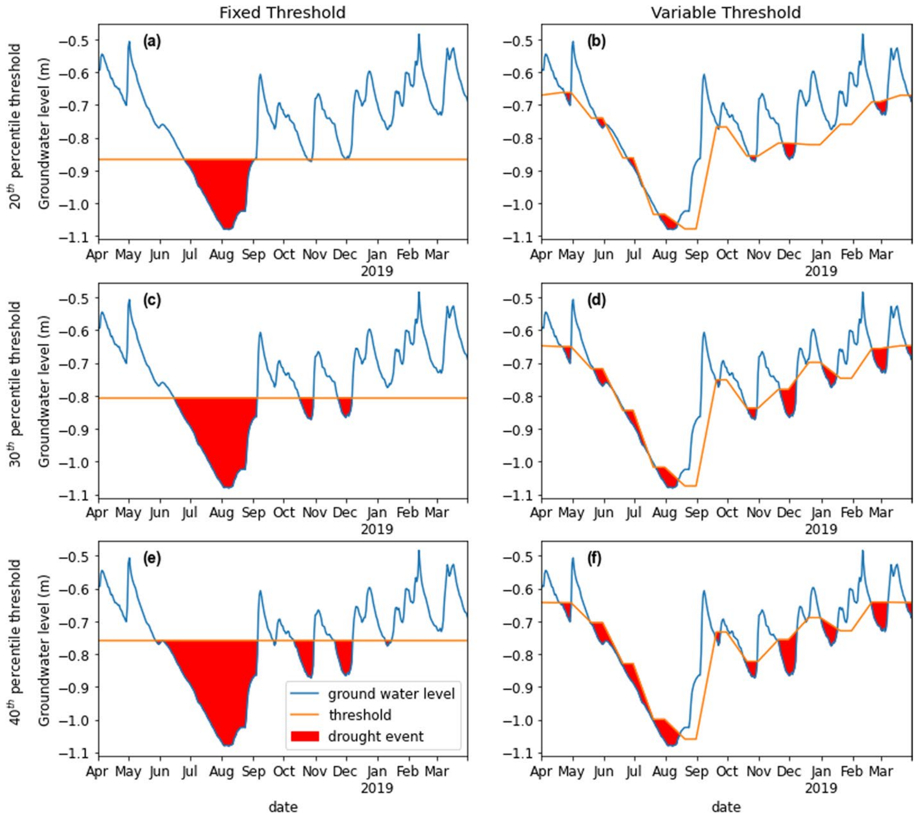

Fig. 6 Identified groundwater drought events using Fixed, and Variable threshold at three different percentiles for well L-PB44 in Binnenstad-Zuid District (ground level: 0.418 m – AOD)

2.10 Sensitivity analysis

As a final step sensitivity analysis was performed to quantify the degree to which the removal of each indicator influences the groundwater drought vulnerability. For these sensitivity analyses, exposure indicators were determined using Variable threshold of 30th percentile. To find the impact of each indicator on the vulnerability result a basic method was applied. Firstly, for each removed indicator the weights of the remaining indicators were estimated afresh, by removing the corresponding row and column from the combined pairwise comparison matrix in AHP. Then, the vulnerability of the area was calculated for each cell in the area. The probability density function (pdf) of the normalized vulnerability is presented in a boxplot and compared with the boxplot of the vulnerability in case all indicators are included in order to find the relevance of each indicator for the vulnerability map.

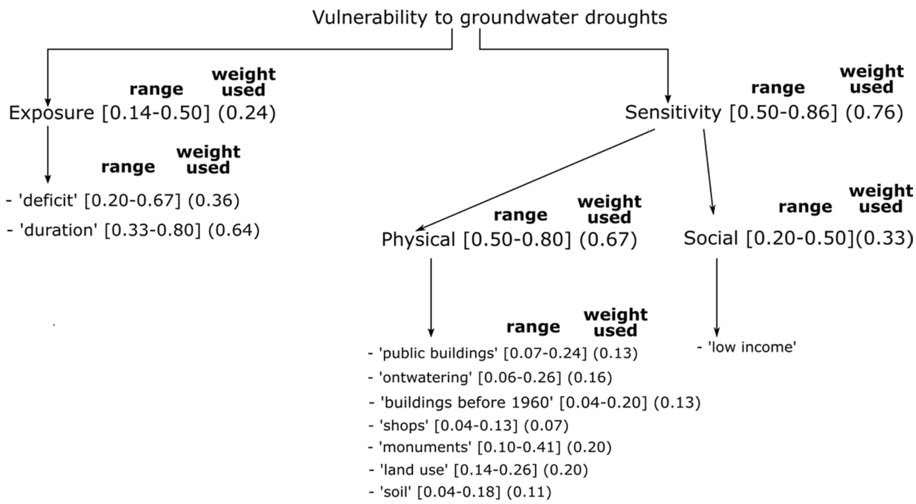

Fig. 7 Vulnerability aggregation for groundwater droughts with the indicators' weights; values in square brackets show the range of the weight and the parentheses the AHP weight used for vulnerability estimation

3 Results

3.1 Exposure assessment

Before analyzing the results of the two threshold methods in Fig. 6, system dynamics of the groundwater level are mentioned. What we see is a typical groundwater level behavior for a lowland city (i.e., Leiden), responding rapidly to rainfall in a well-drained area. The latter explains the rapid drops after the rises in groundwater level. In lowlands, groundwater level is shallow (close to surface level). Rainfall is the driver of groundwater level changes. In the Netherlands, with its moderate sea climate, rainfall is distributed throughout the year. But in the summer of 2018, an extreme drought occurred which explains the large groundwater level drop in August of that year.

Firstly, the results regarding the two different threshold methods for drought exposure identification are presented. These are based on all wells of the four districts. Figure 6 illustrates the droughts based on the well L-PB44. Fixed threshold was able to identify the severity of the drought event of summer 2018 more satisfactorily, as compared Variable threshold. The identified drought events are only a few, concentrated in summer. That is why this fixed threshold method is typically suited for identifying drought events in the dry season; it misses drought events in the wet season.

The Variable threshold method does not have this drawback and identifies drought events over the whole study period. Drought events were identified both in summer and winter. However, the severity of the drought in summer 2018 was underestimated. The fact that only data of one year could be used strongly limited the performance of this method. Had data been available for many more years, threshold levels for the summer months would have been higher and both 'duration' and 'deficit' of the identified summer drought in 2018 would be much greater–and more realistic. A combination of the Fixed and Variable threshold method seems to provide a better insight into the drought exposure in one area. Drought characteristics derived by the Variable threshold method were used for

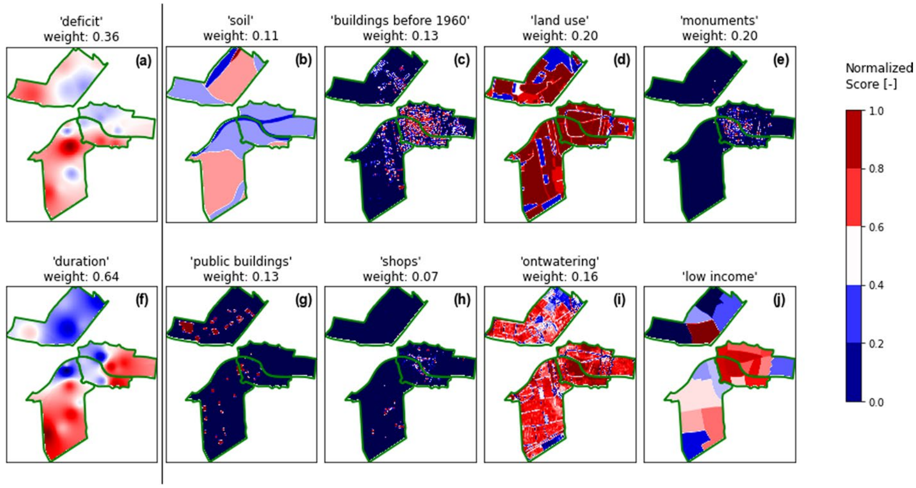

Fig. 8 Exposure and damage sensitivity indicators for groundwater droughts in Leiden; their weights are attached; *the weight of `low income' indicator is not attached to avoid confusion since this indicator was not used for the aggregation of physical damage sensitivity

exposure assessment. Variable threshold was preferred since it provides results throughout the year. This option could be different based on the needs of the research.

Regarding the level of the threshold, the 30th percentile threshold level was selected to quantify exposure. This choice leads to distinct drought periods, without exaggerating the seriousness of such an extreme event in summer and winter months, can be seen in Fig. 6. Drought durations and deficits derived by 20th percentile had quite low values; hence, this percentile was not able to identify long drought events.

3.2 Weights assessment

The indicators used and their weights, as assessed by the AHP, are shown in Fig. 7. For most of the indicators, the experts' weights diverged rather strongly, as shown in more detail in Appendix. Regarding social damage sensitivity, 'low income' was considered the leading indicator, but drought experts found it difficult to value this indicator, resulting in a large range of weights.

3.3 Vulnerability results

Normalized exposure and damage sensitivity indicators are presented in Fig. 8.'duration' values are more pronounced than 'deficit' ones but their pattern in general has some similarities. Two indicators—'land use' and 'ontwatering'—show high scores over a large area. (see Fig. 8d and i). On the contrary, the indicators 'buildings before 1960', 'monuments', 'public buildings', and 'shops' score zero, except for the location

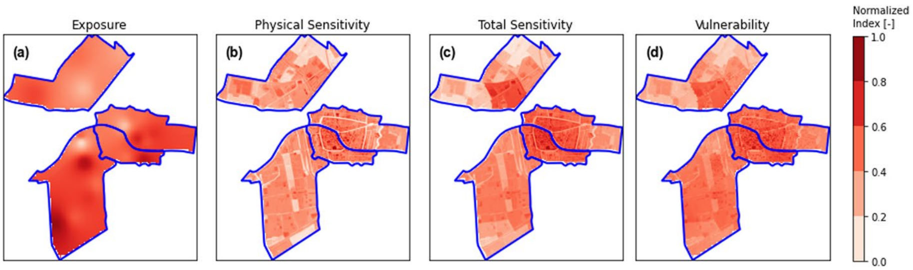

Fig. 9 Exposure, damage sensitivity, and vulnerability to groundwater droughts in Leiden; exposure was assessed with the Variable threshold method, using the 30th percentile

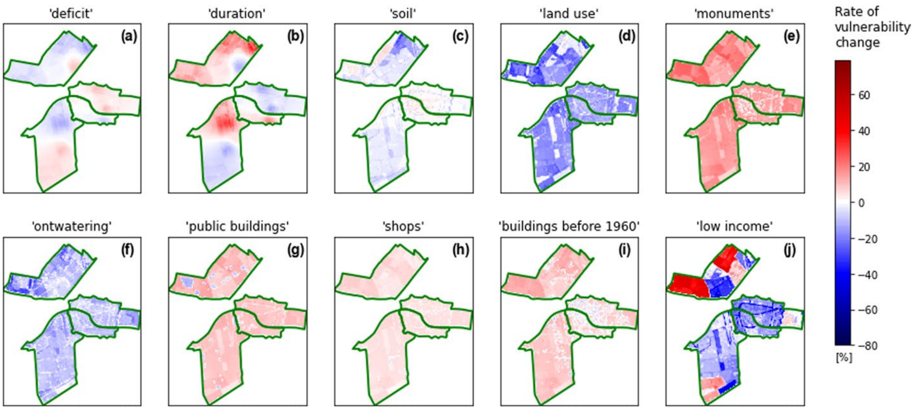

Fig. 10 Rate of vulnerability change (%) due to excluding one indicator regarding groundwater droughts each time

of these buildings; at these sites their normalized score is 1. It is also worth noting that the 'low income' indicator is not as fine in resolution as the other ones since its data was collected at neighborhood level.

Figure 9 illustrates the vulnerability of the districts and its main components. These maps are produced using the normalized scores of the indicators shown in Fig. 8 and the weights produced in the AHP (Fig. 7). The most vulnerable areas for groundwater drought are the old city center, the southern part of the Boerhave District and selected sites in the Bos en Gasthuis area. The vulnerability's pattern follows total damage sensitivity component since its weight (0.76) was larger than that of exposure (0.24). Due to this, the hotspots of exposure are hardly noticed in the vulnerability map. The difference between physical and total damage sensitivity is that the result of the indicator 'low income' is included in total damage sensitivity. For example, part of the Boerhave District turns red due to the low incomes in that part of the town, hindering implementation of adaptation measures by the residents.

3.4 Sensitivity analysis to the vulnerability indicators

How much each indicator affects the final vulnerability product is estimated by removing each indicator and computing the rate of change in vulnerability. The most important findings are highlighted below, in Fig. 10.

Removal of ‘monuments’ leads to a large increase of vulnerability over the whole study area (see Fig. 10e). This is logical, since most of the area has zero value except the sites of the ‘monuments’ whose value is 1. Therefore, when we remove that variable, there is an increase in vulnerability for most area except for ‘monuments’ locations. Vulnerability also rises considerably for removal of ‘duration’, and ‘low income’, but only in specific areas. On the contrary, vulnerability decreases for most of the study area when the `land use’ indicator is not included. `ontwatering’ removal seems to have a negative influence on vulnerability but the drop is smaller than that removing ‘land use ‘. Given that these indicators have high vulnerability for most of the area, their removal leads to a significant decrease. As the weight of ‘land use’ is higher than that of `ontwatering’ removal of ‘land use’ leads to a larger change. Regarding the indicators ‘public buildings’, ‘shops’, and ‘buildings before 1960’, there is a minor decrease at the location of these objects, but for the rest of the area a slight increase occurs. Furthermore, ‘soil’ does not influence vulnerability significantly as its weight is not high either. Any increase or decrease of the vulnerability is the result of the normalization and the weighing of each indicator in the aggregation process. The vulnerability map should therefore be interpreted in a relative sense; differences are to be interpreted by analyzing which factors (indicators) cause a certain site to have a high or low normalized score.

The vulnerability change presented in the maps in Fig. 10 can also be presented in vulnerability boxplots (See Fig. 11). The weights of indicators used in each case are presented in Table 3 in Appendix. ‘land use’ and ‘monuments’ had the largest absolute change in median value of the vulnerability, followed by ‘low income’. It is worth mentioning that there are many outliers for ‘land use’ and ‘low income’. The median almost did not change for `deficit’ and ‘duration’. Even though in Fig. 10b vulnerability change varies spatially when ‘duration’ is excluded, most of the variation is due to outliers, as illustrated by the third boxplot of Fig. 11.

An increase of variation (difference between 25 and 75th percentile—box plot size) was noticed for `monuments’ and `public buildings’. On the other hand, negative variation is the highest when ‘land use’ and ‘low income’ removed. ‘ontwatering’ is also a sensitive indicator but to a lesser degree. Therefore, based on Figs. 11 and 12, ‘low income’, ‘land use’, and ‘monuments’ are the most important indicators in this vulnerability analysis as they stress vulnerability differences. However, the fact that the differences with other indicators are not pronounced and the high number of outliers decrease the certainty of the statement. The analysis benefits from inclusion of other indicators, even if the results are not very sensitive to inclusion; they help to create a deeper understanding of the vulnerability to groundwater drought.

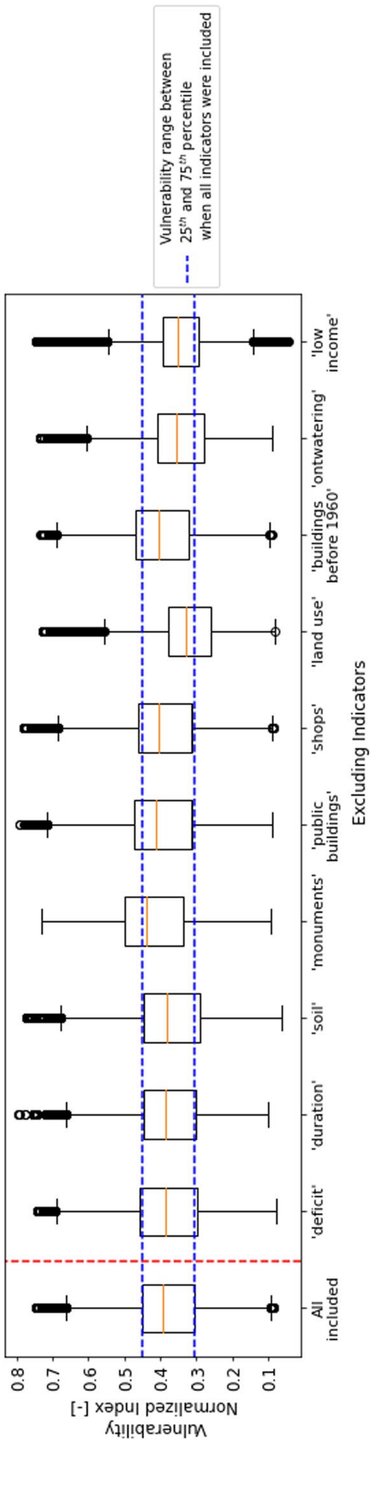

Fig. 11 Boxplots for vulnerability to groundwater droughts when each indicator was excluded

4 Discussion

An urban drought categorization framework is proposed which categorizes drought vulnerability from the perspective of the urban water system and the functions supported by each of its elements. This results in four drought classes, i.e., groundwater, soil moisture, surface water and water supply drought. This framework is straightforward and may be applied in any region. It may help policy makers identify if an urban drought affects their city and what its category is. Identifying how each drought category affects a city leads to a profound analysis of the city's vulnerability and enables prioritizing adaptation actions. As a first step, a vulnerability assessment method for groundwater drought was elaborated and applied in a case study in Leiden, the Netherlands, in a desk study.

As usual, vulnerability to groundwater drought was quantified as the product of exposure and damage sensitivity. Exposure was quantified in terms of groundwater level deficit and duration of the drought period. In order to estimate this deficit and duration, two methods were evaluated. A Fixed threshold method could identify drought events satisfactorily only for the summer period, when the groundwater levels are low. This can be useful for projects related to construction, and foundation of buildings; but unusually low groundwater periods in other seasons are missed. Deficit and duration identified via the Variable threshold method provide estimates of deficit and duration in all seasons. Lack of data in the current study—only one full year was available—however hindered a good application of this method. In general, a combination of Fixed and Variable threshold seems to be appropriate to characterize two drought characteristics, i.e., deficit and duration in a specific area, as both methods quantify the indicators from a different perspective; The Fixed threshold methods considers the absolute minimal groundwater levels, while the Variable threshold method differentiated the perspective to extreme lows in each month. In the Leiden case their combined use provided a deeper understanding of groundwater drought exposure than using only one of the two.

The best way to assess the level of the threshold that is to be used for droughts identification is with the help of stakeholders based on the drought-threatened water functions for the city. However, this approach is more complicated than it looks like. Different water functions would require a different threshold but only one threshold can be applied. In this desk study we had to skip this consultation and used the 30th percentile groundwater level to define exposure deficit and duration.

Vulnerability to groundwater droughts was determined via aggregation of exposure and damage sensitivity, following the framework of Fritzsche et al. (2014), but with some modifications. AHP was used to determine indicators' weights, building on the expert judgments of eight senior experts in this field. One main finding is that though the methods to assess groundwater drought exposure resulted in very different estimates of deficits and durations, this influenced vulnerability only to a limited degree, due to the low weights of the exposure indicators versus the weights of the damage sensitivity indicators.

For the Leiden case the damage sensitivity indicators, \`land use', 'monuments' and \`low income" are useful for vulnerability estimation since vulnerability proved most sensitive to their removal. The latter indicator shows whether the residents can afford possible repairs in their houses in case damage occurs. Their large spatial variation in vulnerability make it easier to identify problem areas and set priorities.

A good vulnerability indicator is one variable which may be quantified and affects vulnerability considerably. Out of eight damage sensitivity indicators tested, only three of them seem to be useful; the other were less relevant to estimate groundwater vulnerability. However, in other cities, different indicators may be more relevant. The system behavior of vulnerability over cities varies and any conclusion about the selection of indicators cannot be generalized.

The uncertainty of vulnerability is related to indicators' weights. When one indicator is removed, there is no difference in input data of other indicators. The indicators weights' differences are subtle–see Table 3 in Appendix for details. This slight change of weights accounts for slight changes in vulnerability.

In general, the uncertainty of input data is related to the accuracy of the recorded data obtained from local authorities and openstreetmap.org. No information was available about this accuracy. Input data derived from point data—such as exposure indicators derived from groundwater levels observed in wells—contain further uncertainty due to interpolation between these points. The output uncertainty from GIS overlay may be specified via error propagation or simulation methods (Shi et al. 2004). Given that output of one overlay is used as input for another overlay, error propagation may be applied as many times as the aggregation levels (i.e., physical damage sensitivity, total damage sensitivity, exposure, and vulnerability). In the current case, aggregation is a linear function which means that it may be derived analytically. This method is not computationally demanding but the main drawback is that the results are approximate (Alesheikh and Abbaspour 2008). This is why the output uncertainty was not applied.

4.1 Evaluation of the proposed vulnerability method

The main advantages of the method to determine groundwater drought vulnerability in cities as applied in this project include: (i) simplicity, (ii) limited computational cost, and (iii) fine spatial resolution level. The method is intuitive; therefore, policy makers would be able to cooperate with water managers, e.g., to assess indicator weights. This can lead to a more critical assessment of the inputs and results and, in the end, better decisions. Furthermore, this method is not computationally expensive, given that only observed deficit and duration are used as exposure indicators and some simple GIS operations are to be applied. However, the method is data-intensive if areal extent and frequency of droughts are used as exposure indicators, and various spatially distributed damage sensitivity indicators are used. This high-resolution spatial damage sensitivity data however allow for a high spatial resolution of the vulnerability maps.

The uncertainty of the measured groundwater input data depends on the accuracy of the measurement gauges used. The missing values due to technical problems to the gauges decrease the quality of the input data. There is also spatial uncertainty in the results. Spatial interpolation via inverse distance weighting (IDW) was applied to determine the exposure indicators (deficit and duration) for every spot on the study area given that there is no groundwater model of Leiden available. IDW determines the values of unknown locations by using the weighted average of neighboring points. The fact that only one year of groundwater level data could be used is a critical limitation to the reliability of the results of the case study. Multi-annual groundwater data series are required in next applications of the method.

The number of consulted drought experts in the AHP was limited and their opinion on the weights of each potential indicator diverged. Therefore, there is uncertainty about the indicators' weights in the case study. It could be wise to discuss and re-evaluate the results of the AHP with the experts in order to seek more consensus on the weights and repeat the vulnerability assessment to strengthen their support and so reduce the uncertainty of the results.

Regarding weights' consistency, the consistency ratio was lower than 0.1 which means that experts compared the indicators consistently and the weights produced are not random. Another point in favor of increasing weights' credibility is that the combined matrix from experts was computed via geometric mean which provides more accurate results than arithmetic one when there is high variability in individual matrices. However, this cannot compensate for the limited number of experts used.

Using many indicators is undesirable for vulnerability assessment since it complicates the pair comparison regarding weights in the AHP method. Additionally, the fewer indicators there are, the lower the cost and effort required for vulnerability determination. Minimizing the number of indicators without losing information is to be strived for.

Validation of the resulting vulnerability map was very limited due to lack of data. Plausibility of the map was checked with the local experts involved in the AHP weight assessment and approved. More robust ways of validating the map would focus on the uncertainty in exposure and damage sensitivity data. Only one year of groundwater level data was available. Validation of the exposure data would be possible by using data from other recent years. And an inventory with infrastructures (including their locations) and the severity of their damages due to subsidence would be helpful to assess uncertainty in damage sensitivity. Subsidence is one of the consequences of groundwater drought. However, this damage information does not exist. Validating the approach is done by repeating the study for other urban areas. This is recommended as a next step; the current study provides only a proof of concept. A further dialogue with the experts on the indicators and their weights and wider tests and applications of the method are required to validate the resulting vulnerability map for policy making.

Transferability of the method is limited. Transferability may split into two categories: (i) to other cities, (ii) other scenarios. The latter is even categorized into (a) climate scenarios, and (b) urban developments. If it comes to cities, each step would lead to different results and the vulnerability map would be different. The method would be performed from the beginning with new data. The indicators and their weights would be different, since the local experts' perspectives on vulnerability may be different. Regarding climate scenarios, we cannot transfer the results, since a groundwater model is necessary to quantify the changed exposure; groundwater levels could be determined for different climate scenarios resulting in different vulnerability maps. As for urbanization scenarios, changing the input data can lead to different results. For instance, buildings erected before 1960 could be changed into newly built areas. This would lead to a different vulnerability map.

4.2 Assumptions of damage sensitivity Indicators

Another point which raises discussion is the quality of damage sensitivity data. Two assumptions increase uncertainty:

(i) Dwellers income is relevant for the vulnerability. But tenants are not responsible for repairs related to drought damages. And the percentage of rental houses in some parts of the pilot areas is high. Their income is therefore irrelevant for the damage sensitivity.

(ii) The assumption that buildings erected before 1960 are all built on wooden poles. This might be incorrect. Foundations might have been repaired or replaced. Consequently, even if such damage sensitivity data are recorded at a fine spatial resolution, the aforementioned assumptions can bias the vulnerability results.

4.3 Comparison with studies regarding urban areas

Most literature regarding vulnerability estimation to droughts is about rural areas; there is hardly any studies regarding urban areas. One important outcome of the present analysis is that the weight for social damage sensitivity for groundwater droughts was half as high as physical damage sensitivity. This result seems not necessarily in-line with the results reported by Chang et al. (2015) who found that in some Chinese cities social damage sensitivity contributed the most to vulnerability. Apart from cultural differences, a possible explanation for this difference could be that entropy evaluation was applied to estimate weights in that study, while for the current one Analytical Hierarchy Process (AHP) was employed.

Two other differences between the current study and others are: (i) the scale level of analysis, and (ii) the fact the other studies were about droughts in general. Regarding (i), in the studies by Chang et al. (2015) and Yuan et al. (2015), vulnerability among different cities were compared while in the current analysis districts in one city were compared. As for element (ii), the previous two studies were not specific to a drought category.

4.4 Comparison with studies regarding rural areas

Comparing the current study to those focused on rural areas, two main differences are noticed. Firstly, the number of aggregation levels was different. In the current analysis for groundwater droughts, four levels of aggregation were applied (i.e., exposure, physical damage sensitivity, total damage sensitivity, and vulnerability). Social damage sensitivity consisted of only one indicator and therefore needed no aggregation. On the contrary, on the studies conducted by Gurwin (2014), Kim et al. (2015), Thomas et al. (2016), only one aggregation was performed including all indicators. Our approach highlights the importance of the weights in the vulnerability assessment. For instance, the weight for one exposure indicator is high but the weight of the `exposure' component over damage sensitivity is not. Consequently, the exposure indicator does only limitedly influence vulnerability. If only one aggregation level was considered, exposure's influence to vulnerability would have been larger. Moreover, it is more transparent to use more aggregation levels, since drought experts can compare the indicators in AHP more easily. It is worth noting that for this reason Savari et al. (2022) have used six aggregation levels in their study about South-East Iranians farmers—one for each dimension of vulnerability (economic, sociocultural, phycological, technical-environmental, and infrastructural) and the total aggregation.

For the majority of the studies regarding vulnerability to agricultural droughts (e.g., Gurwin (2014); Kim et al. (2015); Nasrollahi et al. (2018); Shahid and Behrawan (2008); Thomas et al. (2016)), standardized indices were considered for exposure estimation. The frequency of meteorological droughts in combination with their severity were used as exposure indicators. None of these studies used threshold method. Standardized indices such as SPEI and SPI were also used for drought vulnerability of Sao Paulo and Iran based on the study of Henrique et al. (2021) and Alamdarloo et al. (2020) respectively.

The current pilot application of the method focused on a developed country, whereas the majority of drought studies focus on developing areas. In developing countries, they may be mostly interested in agricultural droughts, since their economy is highly dependent on the primary sector. However, some cities in these countries are exposed to groundwater urban droughts, too. The damage sensitivity of these cities would probably be greater than those in developed countries, which means that they may suffer severe damages from droughts. Urban drought in developing countries should therefore be a research priority.

5 Conclusion

The purpose of this research project was (i) to create a framework to categorize urban droughts, (ii) to develop a method to estimate vulnerability of cities to groundwater droughts and (iii) to demonstrate its application in a case study in the lowland city of Leiden, the Netherlands. This results in four urban drought categories, i.e., groundwater, soil moisture, surface water and water supply drought. Except for water supply drought, drought in cities has been hardly studied, even though the consequences of droughts can be devastating for their residents in a variety of sectors such as economy and health.

For estimating the vulnerability of an urban area to groundwater drought, a modified version of the methodology suggested by Fritzsche et al. (2014) is used, considering both exposure, and damage sensitivity components but using AHP to assess the weights of the various indicators.

Regarding the quantification of exposure, the Fixed and the Variable threshold method identify deficit and duration of groundwater drought from a different perspective. The Fixed threshold methods considers the absolute minimal groundwater levels, while the Variable threshold method differentiates the perspective to extreme lows in each month. Application of the combination of both provided insight into drought exposure of our case area from both perspectives.

Physical and social indicators were used to quantify the damage sensitivity of the case study area. Weights of the indicators were assessed using AHP, so that exposure and damage sensitivity data could be aggregated into one vulnerability map. The damage sensitivity indicators, 'land use', 'monuments' and `low income' contributed the most to vulnerability

Table 1 Data gaps of groundwater stations where interpolation was applied

Station	largest gap (days)	Total Gap (days)
Binnenstad-Zuid		
L-PB42	27	50
L-PB44	4	4
L-PB46	4	4
Bos en Gasthuis		
L-PB71	32	39
L-PB72	8	12
L-PB73	24	29
L-PB80	4	6
L-PB82	17	28
L-PB83	4	4
Binnenstad-Noord		
L-PB49	4	4
L-PB50	4	4
L-PB54	9	13
L-PB55	37	42
L-PB56	39	44
Boerhaave		
L-PB08	40	45
L-PB09	4	4
L-PB12	9	13
L-PB13	7	14
L-PB14	68	88

variation over the area. For several reasons the resulting vulnerability map could not be validated. The result looks logical and demonstrates the operability of the method, but more data are to become available to proof the local differences in the vulnerability of the pilot area to groundwater drought.

Table 2 Weights for 'land use' and 'soil' classes

Land use		Soil	
Class	Weight	Class	Weight
Built-up	1	trench and trench deposits	0.4
Water	0	old dunes	0.2
Company sites	0.8	Holland peat	1
highway	0.8	deposits	0.6
Recreation	0.2	tidal basin/tidal deposits	0.6
Semi-built	0.5	river bed	0
Agriculture	0.2		
Railway	0.9		
Forest	0.2		

A remarkable result of the study is that vulnerability of the area follows the spatial pattern of damage sensitivity more than the pattern of exposure. This due to the larger weight of the damage sensitivity than exposure indicators. Consequently, emphasis needs to be laid on damage sensitivity data collection, in addition to assessing exposure. The need for a

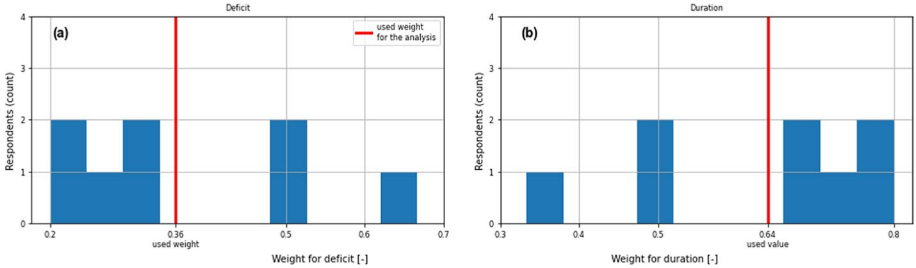

Fig. 12 Weight histogram for exposure indicators regarding vulnerability of the Leiden pilot area to groundwater drought

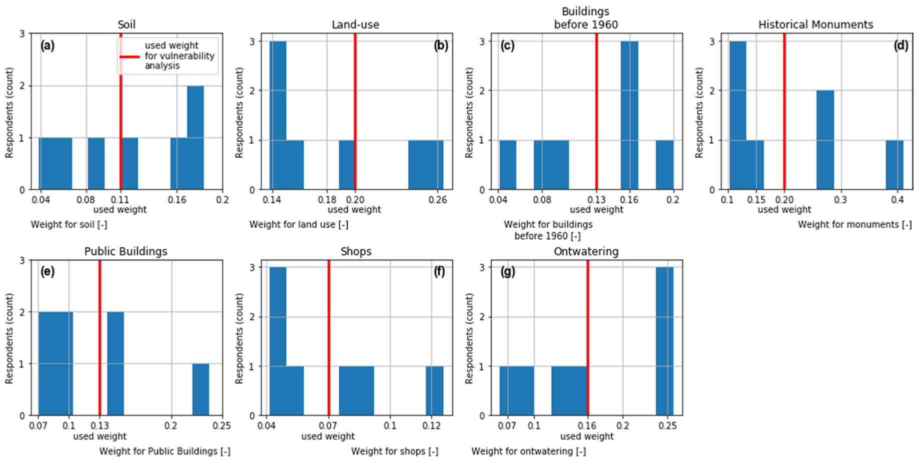

Fig. 13 Weight histogram for physical damage sensitivity indicators regarding vulnerability of the Leiden pilot area to groundwater drought

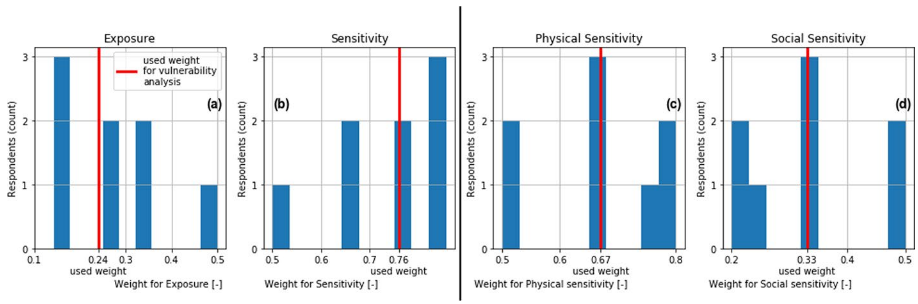

Fig. 14 Weight histogram for aggregated components regarding vulnerability of the Leiden pilot area to groundwater droughts

sophisticated technique for exposure assessment may be less relevant when the availability of reliable damage sensitivity data is the bottleneck in the vulnerability assessment.

Estimating vulnerability at fine spatial resolution can lead to timely drought damage sensitivity recognition and an effective preparedness plan at city level. Hotspots of vulnerability can be identified and, consequently, targeted and cost-effective adaptation measures can be planned and implemented, based on the local needs for vulnerability reduction.

Appendix

Data gaps of study area districts

See Table 1

Land use classes

See Table 2

Table 3 Weights of indicators (dimensionless) when (i) all indicators are included (first column) and (2) each indicator was removed (the other columns)

Soil'	0.11	–	0.14	0.13	0.11	0.15	0.14	0.13
Monuments'	0.20	0.22	–	0.23	0.22	0.24	0.22	0.25
'Public buildings'	0.13	0.15	0.16	–	0.14	0.15	0.15	0.16
Shops'	0.07	0.08	0.08	0.08	–	0.08	0.08	0.08
'Land use'	0.20	0.25	0.25	0.23	0.21	–	0.22	0.24
Buildings before 1960'	0.13	0.14	0.16	0.14	0.13	0.17	–	0.15
Ontwatering'	0.17	0.20	0.20	0.19	0.18	0.21	0.19	–

Histograms of indicator weights based on drought experts' pairwise comparison

See Figs. 13 and 14

Consistency ratio for AHP assessed weights

The robustness of the AHP weights' estimation was evaluated by assessing the consistency ratio (see Formula 1) of the experts' judgment. It is the ratio of the consistency index (CI) of the matrix (see Formula 2) and the random index (RI), that is the consistency index from a large sample of matrices which produced in a random manner) (Saaty 1987). The random index depends on the number of indicators.

$$CR = \frac{CI}{RI} \tag{1}$$

where CI: consistency index, and RI: random Index

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{2}$$

where λ_{max}: principal eigen value, and n: number of indicators.

Weights of indicators in the sensitivity analysis

See Table 3

Indicators weights of exposure are not presented in the table since exposure contains only two indicators; that means when one indicator was removed the other one's weight is one.

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Declarations

Conflict of interest Authors Ilias Machairas and Frans van de Ven declare they have no relevant financial or non-financial interests to disclose.

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