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Assessing Drought Susceptibility and Risk using Dual Multi-Criteria Decision-Making Models

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Abstract

Droughts, characterised by insufficient precipitation relative to evaporation, pose significant challenges for disaster preparedness and mitigation. This study investigates the integration of Remote Sensing (RS) and Geographical Information System (GIS) techniques to map drought-prone regions in Rehoboth, Namibia. It employs two Multi-Criteria Decision-Making (MCDM) methods, namely, the Multi-Influencing Factor (MIF) and the Analytical Hierarchical Process (AHP), to assess factors influencing drought severity. Eight (8) key parameters, including rainfall, slope, drainage density, soil type, normalised difference water index, normalised difference vegetation index, land use / land cover, and land surface temperature, serve as input variables for generating thematic maps representing drought-related factors. The study calculates the weightings of these factors using MIF and AHP methodologies, thereby facilitating a weighted overlay analysis and the creation of drought susceptibility maps. According to the AHP-based model, severe drought-prone areas in the study area cover 0.68%, moderately prone areas, 12.24%, and slightly prone areas, 87.09% of the region. By contrast, the MIF method indicates severe drought-prone areas at 0.12%, moderately prone areas at 12.8%, and slightly prone areas at 87.08%. A comparative analysis demonstrates the consistency and reliability of the results produced by both methods. The findings provide valuable insights for stakeholders and policymakers, thereby contributing to the development of effective drought mitigation strategies and sustainable resource management.

***Keywords**: Drought susceptibility mapping; Risk assessment; Remote Sensing (RS); Geographical Information System (GIS); Analytical Hierarchical Process (AHP); Multi-Influencing Factor (MIF)*

1. Introduction

Drought is a prolonged period of abnormally low precipitation that leads to water scarcity and results in dry conditions and a shortage of water resources. It is a natural phenomenon that occurs when there is a lack of rainfall over an extended period, which causes adverse impacts on agriculture, the water supply, ecosystems, and socio-economic activities (Iilonga & Ajayi, 2025). It manifests over a wide range of timescales and spreads gradually. According to Lai (2022), droughts account for 15% of all natural disasters that took place between 1970 and 2019, making it the primary cause of about 650,000 fatalities worldwide. Droughts can vary in duration and intensity, ranging from short-term dry spells to prolonged periods of severe water shortage. They can occur regionally, impacting specific areas or entire regions and can be classified into four (4) main types, namely, meteorological, agricultural, hydrological, and socioeconomic drought (Iilonga & Ajayi, 2025). Meteorological drought is the level of precipitation deficiency over a particular period. It simply denotes a lack of precipitation when the amount of precipitation in a certain area is less than 25% of what is considered typical. Agricultural droughts are experienced when crops do not receive the necessary amount of soil moisture to promote forage and crop growth. This ties several hydrological or meteorological drought characteristics to their effects on agriculture, concentrating on precipitation deficits, discrepancies between actual and predicted evapotranspiration, soil, soil water deficits, and decreased groundwater or reserve levels (Murad, 2010). On the other hand, hydrological drought affects stream flow, soil moisture, water availability from river, lake, and groundwater sources, and is caused by weather-related factors, increased human water demand and consumption, changes in land use, soil depletion, and water reserves that are below quantitative measurements (Al Arazah, 2017). Socio-economic drought occurs when water supply from a regional water resource system cannot meet the demand for water (Liu *et al*., 2020).

Irrespective of its type, drought poses a grave threat to the social sector as it leads to forced migrations, emanating from life-threatening circumstances such as famine and crisis (Adaawen *et al*., 2019; Abel *et al*., 2019; Reid, 2023). This natural disaster contributes to malnutrition and hunger through diminished agricultural production, thereby leading to food insecurity and putting human health at risk. Furthermore, when dust levels increase − harmful to individuals with respiratory conditions –, the quality-of-life declines. According to Shukla *et al*. (2020), drought has been the primary cause of shortages in global grain outputs relative to consumption in the first half of the 21st century and has posed a significant threat to food security. Water scarcity also harms biodiversity, as poor soil quality and lack of water limit plant growth, while animals suffer from dehydration, adding to the risk of endangering species (Tzanakakis *et al*., 2020). In lengthy or prolonged drought periods, the chances of destructive wildfires increase. They have far-reaching consequences for the economy, environment, and society, including the destruction of neighbourhoods, crops, and habitats (Desbureaux & Damania, 2018). Ultimately, these factors cause financial hardship, with significant negative consequences for critical industries such as tourism, resulting in reduced employment opportunities and income loss (Kalaba, 2019).

Recent events in Namibia present a stark illustration of the severe impacts of drought and the complex challenges it presents. On 22 May 2024, the Government of Namibia declared a state of emergency in response to what has been described as the most severe drought the country has experienced in a century. The crisis has left one in five Namibians food insecure, prompting over 331,000 households to enrol in a government-funded drought relief programme. Despite allocating EUR 40 million to this programme, Namibia faces a significant funding gap of EUR 25 million which highlights the economic strain that drought can place on affected nations. The severity of the situation led to an extraordinary summit of the Southern African Development Community (SADC) on May 20, 2024, where Namibia's President appealed for international assistance to address the crisis (European Commission, 2024).

In response to these dire circumstances, Namibia implemented a controversial culling programme, involving 723 wild animals, including 83 elephants. This programme aims to mitigate the impact of drought on both wildlife and human populations. The meat from these animals is being distributed to individuals facing food insecurity, thereby addressing their immediate needs whilst also attempting to reduce the human-wildlife conflicts exacerbated by limited resources. As of June 2024, Namibia had depleted 84% of its food reserves, with projections indicating that close to half of the country's population will face severe food insecurity in the coming months. The culling programme, which also includes other species such as Hippopotamuses, Buffalo, Impala, Blue Wildebeest, Zebra, and Eland, yielded over 56,800 kilograms of meat for the drought relief programme. This case highlights the complex interplay between drought, food security, wildlife management, and human welfare, thereby demonstrating the far-reaching consequences of prolonged water scarcity and the challenging decisions faced by affected regions (NBC News, 2024).

The impact of drought depends on the ability of a region to recover (Marengo *et al*., 2021). Different approaches have been explored to design a reliable recovery programme to mitigate the impact of drought. Critical to this programme is the need to develop frameworks that will provide precise information pertaining to the severity of droughts over time.

Satellite remote sensing (RS) products, in conjunction with Geographic Information Systems (GIS), are indispensable for effectively monitoring natural disasters and disaster-related events globally. They offer a comprehensive approach to studying and assessing drought (Van Westen, 2000) in that they integrate and analyse diverse data sources. As such, as opposed to other methods, they are more user-friendly in assessing drought zones. In mapping out drought-prone areas and their influencing factors, this study integrates GIS and Remote Sensing with multi-criteria decision-making (MCDM) approaches, specifically, the Multi-Influencing Factor (MIF) and Analytical Hierarchy Process (AHP) methods. Although there is a dearth of studies on both methods for deriving drought-prone zones, MIF and AHP offer distinct advantages. The MIF approach supports decision-making by analysing the spatial relationships between the pertinent independent and dependent variables, with due consideration given to the major and minor factors affecting drought. By contrast, the AHP method is the leading MCDM method (Ajayi *et al*., 2022), and, according to Palchaudhuri & Biswas (2016), it assists in prioritising decision-making criteria through pairwise comparisons. The afore-mentioned method addresses complex drought vulnerability challenges by systematically breaking down problems and minimising personal bias, thereby producing rational results. AHP makes it possible to rank options in a systematic manner − even when there is insufficient quantitative information or when the outcome involves only a few percentage figures that are easily computed and understood (Hartwich, 1999, Ramafikeng *et al*., 2025). AHP does not require historical datasets; rather, it deals with both the qualitative and quantitative components of a decision-making problem by combining experience, intuition, and physical facts to assist decision-makers in coming up with the most effective answers (Canco *et al*., 2021). By using different qualitative techniques, while adhering to the same methodological research framework, it is possible to improve on the quality and depth of the drought modelling process (Justesen & Mik-Meyer, 2012). Since varied approaches reveal various viewpoints and opinions (Essén & Sauder, 2017), these components informed the choice of using both MIFs and the AHP method in this study.

To identify drought-prone areas requires an analysis of several criteria in a pairwise comparison matrix. Weighted overlay analysis, within GIS and using weights derived from the multi-criteria decision analysis (MCDA) methodology, makes it possible to identify drought-prone zones in the study area. The assessment relies on various drought indicators, such as drainage density, slope, soil type, land surface temperature (LST), land use/land cover (LULC), the Normalised Difference Vegetation Index (NDVI), the Normalised Difference Water Index (NDWI), and rainfall. These indicators activate drought responses when their values reach certain thresholds, thus serving as the foundation for a drought plan that links the causes of droughts with the corresponding solutions (Steinemann & Cavalcanti, 2006). This study investigates the severity of droughts in Rehoboth, a town in the Hardap region of Namibia, using GIS, remote sensing, and MCDA approaches. It evaluates key drought factors in the area and compares the effectiveness of AHP and MIF methods for modelling drought severity. The expected outcomes will benefit decision-makers, individuals, and communities involved in agricultural activities, water resource management, and water conservation efforts.

2. Study area

Rehoboth is a town located in the Hardap region of Namibia. It lies between latitudes 23° 13' 13" S and 24° 14' 59" S, and longitudes 16° 25' 10" E and 17° 18' 23" E and is approximately 84 kilometres south of Namibia's capital city, Windhoek. At an altitude of 1,385 metres above mean sea level, the town is situated along the dry, sandy banks of the Rehoboth River. The dry, sparsely populated area in the central highland in which Rehoboth lies is mainly mountainous, with stony hills and sand-filled valleys as its dominant physiography. The 2011 Namibian Population and Housing Census shows that the population of the study area increased from 21,378 in 2005 to 28,843 in 2011, with the population at that stage estimated to increase to 41,123 in 2023, according to the Namibia Statistics Agency.

Rehoboth consists of Rehoboth Rural, Rehoboth Urban East, and Rehoboth Urban West. While Rehoboth Rural comprises all the small settlements and farms surrounding Rehoboth such as Kauchas, Kobos, Groendraai, Tsunamis, Blokwater, Omomas, Schlip, Lammewater, Karanas, Klein Aub, Witkop, and Rietoog. On the other hand, Rehoboth Urban East consists of all the suburbs in Rehoboth, such as Banhoff, which is located east of the National B1 road.

Damage to crops caused by drought episodes in the Rehoboth area has resulted in wilting and has negatively impacted crop production. Also, limited grazing areas and drinking water supplies have resulted in high livestock mortality rates. As reported in the Namibia Vulnerability Assessment Report of 2022/2023, similar conditions in the northern areas of Namibia bear testimony to the impacts that drought has had on agricultural production, which led to malnutrition in the area in October 2023. The March 2024 projection for Nashandi (2023) shows that the Hardap region is expected to enter the Phase 2 stressed phase in the Integrated Food Security Phase Classification (IPC). While the Government has planned a drought relief intervention in terms of food support to the region, it expects the food security situation to worsen by at least four percent (4%). Figure 1 shows a map of the study area.

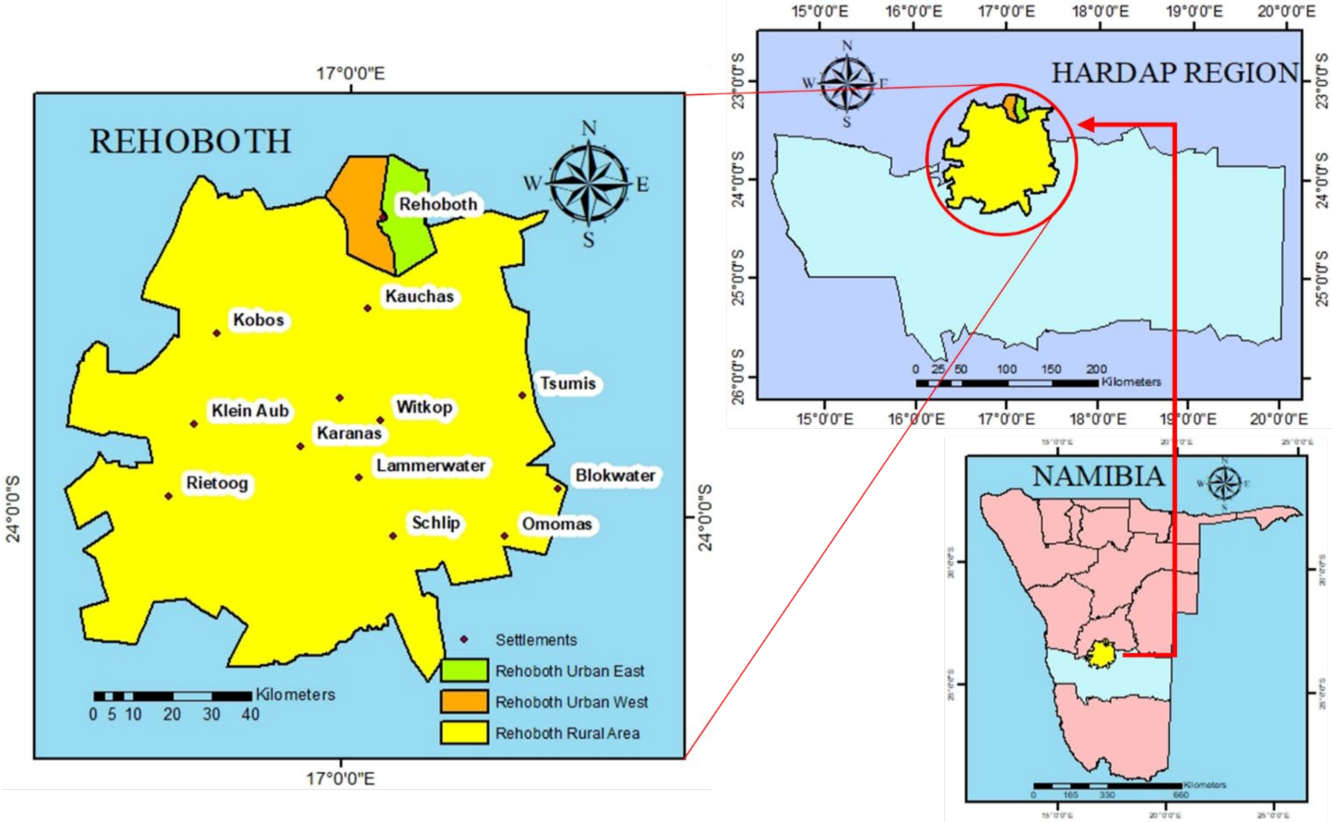

Figure 1: Study Area

3. Materials and Method

3.1. Data collection and processing

The procedures used in this study are presented as a flowchart (see Figure 2) while the data, including the data sources and the software, are presented in Tables 1 and 2. Both spatial and non-spatial data were used, with the spatial data pertinent to the Digital Elevation Model and the Landsat 8 images, and the non-spatial data pertinent to rainfall, soil type, and stream network.

Table 1: Details of data used and their sources

Data	Data Source	Generated Map/Extracted Data type
SRTM DEM (30m resolution)	NASA Earth Data	Slope and Drainage Density Map
Landsat 8 Collection 2, Level 1	USGS	LULC, NDVI, NDWI and LST Map
Soil Type	FOA	Soil Type Map
Rainfall	Ministry of Agriculture, Water and Forestry	Rainfall Chart
Stream Network	Digital Namibia	Drainage Density

Table 2: Types of software used and their purposes

Software	Purpose
QGIS 3.30	Supervised image classification to produce a land use / land cover map of the study area
ArcGIS 10.5	Production of maps to represent factors that contribute to the occurrence of drought zones, a weighted overlay map to show pertinent factors of concern, and a drought-prone map of the study area.
Microsoft Excel	Calculation of criteria weights needed for AHP

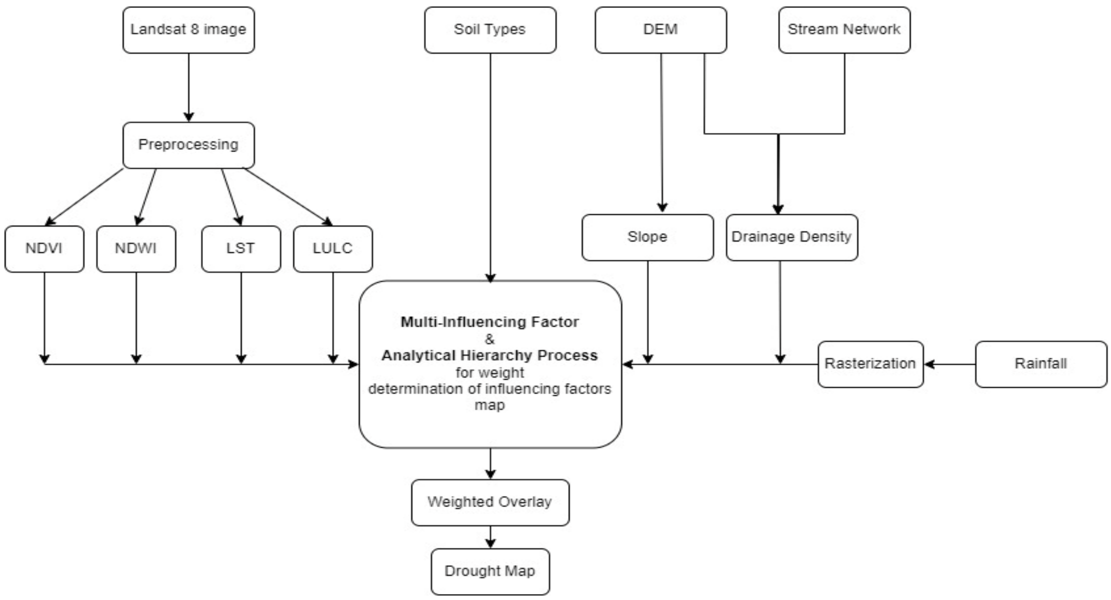

Figure 2: Study Workflow

The study downloaded the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) from the USGS platform. Being in the form of tiles with a 30 m resolution value, the DEM platform served to simplify the data download process in that it extracted slope and drainage density, two of the factors contributing to drought in the study area. We then proceeded to downloadLandsat-8, Collection 2, Level 1 images from the portal of the United States Geological Surveys (USGS) on 9 May 2023, with scene identifiers LC81780762023129LGN00 and LC81780772023129LGN00, respectively. We used this satellite dataset to produce the land use / land cover (LULC), Normalised Difference Water Index (NDWI), Normalised Difference Vegetative Index (NDVI) and Land Surface Temperature (LST) maps of the study area. We downloaded soil data from the United Nations' Food and Agriculture Organisation (FAO) platform, while the rainfall data, retrieved from the Ministry of

Agriculture's Water and Forestry Office in Rehoboth, were converted from a CSV file to a shapefile and then rasterised for further analysis. The stream network data, retrieved from Namibia's Geospatial Data platform, were used in conjunction with the DEM, to determine the drainage density of the study area.

3.2. Justification for the methodological approach

We selected the Analytical Hierarchy Process (AHP) in the light of its structured framework for handling complex, multi-criteria decision-making under data constraints. The reason behind this choice was that AHP uses systematic pairwise comparisons that diminish subjective bias in that they quantify the parameter relationships (Mulu, Kerebih & Hailu 2024; Hoque, Pradhan & Ahmed 2020)., AHP uses a consistency ratio (CR) to validate pairwise comparisons. If CR is less than 0.1, the weight assignments are considered logically sound (Ramafikeng *et al*., 2025; Mulu, Kerebih & Hailu 2024; Jabbar, Grote & Tucker, 2019). In that it achieves 87% accuracy in groundwater potential mapping (Mulu, Kerebih & Hailu 2024; Ajayi *et al*., 2022) and correlates strongly ($r^2 = 0.77$) with water quality indices in watershed assessments, AHP has proven to be successful in water-related and drought studies (Jabbar, Grote & Tucker, 2019).

We selected the Multi-Influencing Factor (MIF) method as an additional research method to complement AHP as it emphasises spatial interdependencies between variables, with the focus being on qualitative expert knowledge. We were, therefore, able to identify dominant factors in the drought drivers (Mulu, Kerebih & Hailu, 2024; Fildes *et al*., 2025). MIF allows for nuanced spatial assessments, thereby acting as a rapid screening tool for prioritising the pertinent parameters before the quantitative analysis research phase. By standardising the parameters used to a common scale, we selected the Weighted Overlay Analysis technique to integrate both AHP and MIF outputs into a unified drought susceptibility map (Singh & Devi, 2022). Its ability to handle heterogeneous data types and to allow for scenario testing − by adjusting the weights for sensitivity analysis − makes the Weighted Overlay Analysis technique the best suited technique (Hoque, Pradhan & Ahmed, 2020; Jabbar, Grote & Tucker, 2019). Drought-related studies have also made use of this technique, as in drought-modelling exercises in Bangladesh, where it was validated and identified 77% of the researched regions as moderately to extremely vulnerable to drought (Hoque, Pradhan & Ahmed, 2020). This approach combines AHP's quantitative rigour with MIF's spatial detail, while the weighted overlay delivers practical results.

3.3. Image classification and accuracy assessment

Image classification is a procedure used to categorise pixels in a terrain image into land use or land cover classes based on their different spectral reflectance attributes. The study used the Maximum Likelihood Classifier for the supervised classification of the Landsat 8 images. In cases where the training samples sufficiently represent the mean and covariance structure, this classifier can efficiently distinguish between the classes (Sathya & Baby Deepa, 2017). The output map shows the categorised study area with five different classes, namely, water body, agricultural areas, bare land, areas under vegetation, and built-up areas (see Figure 11). It was possible to assess the accuracy of the image classification by selecting 100 randomly selected sample points, considered in terms of overall accuracy, producer's accuracy, user's accuracy, and the kappa coefficient. The results indicated a 78% accuracy, which is considered acceptable (Congalton, 1991).

3.4. Weighted overlay analysis

The study used the weighted overlay tool in ArcGIS 10.5 to identify the drought-prone zones in the study area by combining all the thematic maps as overlays. During this process, each parameter of the respective thematic maps was ranked and weighted according to the MIF and AHP methods. It is worth noting that the effectiveness of the aforementioned factors for mapping drought vulnerability depends on the reliability and availability of data pertinent to the study area.

3.5. AHP method

We used the AHP method to generate an eight by eight (8 x 8) pairwise reference matrix of diagonals. In this approach, all the parameters were ordered hierarchically to allow for a pairwise comparison in each case. Their relative significance was ascertained using the comparative scale, as suggested by Saaty (1990). It consists of integer numbers ranging from one to nine (1 indicating of equal importance, and 9, of extreme importance) (see Table 3) which show the comparative values for each unit. The remaining values in each row reflect the relative significance of these variables. Using the relative weight matrix and the normalised principal eigen vector, we determined the rank of each parameter (see Table 5). Using the comparison matrix, we calculated the normalised principal eigen vector by dividing the sum of the column values by the corresponding values in the relative weight matrix. The normalised principal eigen vector was subsequently derived by averaging the rows, resulting in percentages that quantify the effects of each thematic layer. The consistency ratio (CR) was used to check the accuracy of the relation: a ratio of less than or equal to 0.1 implies an appropriate reciprocal matrix, while a ratio greater than 0.1 indicates that the matrix should be modified (Yahaya, Ahmad & Abdalla, 2010; Ajayi *et al*., 2022).

Table 3: Saaty's AHP scale and its importance

Scale of importance	Definition	Justification
1	Equally important	Two activities add equally to the objectives
3	Moderately important	Experience and judgement slightly favour one activity over the other
5	Strongly important	Experience and judgement strongly favour one activity over the other.
7	Very strongly important	An activity is strongly favoured, and its dominance is demonstrated in practice
9	Extremely important	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgements	When compromise is needed

The consistency ratio was determined using the expressions presented in equations [1] and [2]:

$$CI = \frac{\lambda max - n}{n-1} \quad [1]$$

$$CR = \frac{CI}{RI} \quad [2]$$

Where, λmax = maximum eigen value; n = number of parameters in matrix; RI = random index value (for n = 8; RI = 1.41).

To ensure the reliability of the weights, it is essential to calculate the consistency ratio using both equations [1] and [2]. To do this, the following steps were followed:

Step 1: Principal eigen value (λmax), λmax is the multiplicative addition of the sum of each row with its respective weight elements.

$$\lambda_{\text{max}} = 2.79(0.32) + 6.02(0.19) + 10.99(0.14) + 16.16(0.08) + 10.49(0.12) + 15(0.07) + 22(0.04) + 20(0.04) = 8.899937321$$

$$\lambda_{\text{max}} = 8.899937321 \approx 8.9$$

Step 2: Computation of C.I, using equation [1]

$$\text{C.I} = \frac{8.9 - 8}{7} = 0.128 \approx 0.13$$

Step 3: Computation of C.R, using equation [2]

$$(\text{CR} = \frac{\text{CI}}{\text{CR}})$$

$$\frac{0.13}{1.14} = 0.092 \approx 0.09$$

$$0.09 \leq 0.10$$

To ensure an appropriate pairwise comparison between the factors and the ranking of their respective classes (see Tables 4 and 5), other sources/literature were consulted, including Palchaudhuri & Biswas (2016), Alharbi *et al*. (2022), and Singh & Devi (2022).

Table 4: Normalised influencing factors

	A	B	C	D	E	F	G	H
Rainfall (A)	0.36	0.5	0.45	0.31	0.29	0.2	0.23	0.25
LST (B)	0.12	0.17	0.27	0.29	0.19	0.2	0.23	0.15
Slope (C)	0.07	0.05	0.09	0.19	0.29	0.2	0.09	0.10
Drainage (D)	0.07	0.05	0.03	0.06	0.03	0.13	0.14	0.15
LULC (E)	0.12	0.08	0.03	0.19	0.1	0.13	0.14	0.15
Soil type (F)	0.12	0.05	0.03	0.03	0.05	0.07	0.09	0.10
NDVI (G)	0.07	0.03	0.05	0.02	0.03	0.03	0.05	0.05
NDWI (H)	0.07	0.05	0.05	0.02	0.03	0.03	0.05	0.05
$\sum_{i=1}^{8}$ Factors	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 5: Pairwise comparison matrix using the AHP method

Factors	A	B	C	D	E	F	G	H
Rainfall (A)	1	3	5	5	3	3	5	5
LST (B)	0.33	1	3	3	2	3	5	3
Slope (C)	0.2	0.33	1	3	3	3	2	2
DD (D)	0.2	0..33	0.33	1	0.33	2	3	3
LULC (E)	0.33	0.5	0.33	3	1	2	3	3
Soil type (F)	0.33	0.33	0.33	0.5	0.5	1	2	2
NDVI (G)	0.2	0.2	0.5	0.33	0.33	0.5	1	1
NDWI (H)	0.2	0.33	0.5	0.33	0.33	0.5	1	1
$\sum_{i=1}^{8}$	2.79	6.02	10.99	16.16	10.49	15	22	20

Equation [2] delivered a Consistency Ratio of 0.09 (9.0%). The eight-factor MCDM implies that the inconsistency of the pairwise comparison is acceptable, as Saaty (1990) suggested, since the CR is less than or equal to 10%.

3.6. MIF method

In the case of the multi-influencing factor method, the same eight parameters influencing the effect of drought events are considered for an assessment of drought severity in the study area. The interrelationships and effects that each parameter has on the other are studied, and a chart, as presented in Figure 3, developed. Each relationship is weighted according to its strength and assigned a weight in terms of "rank", as shown in Table 7. The representative rank of a factor in the potential zone is the sum of all weight values applicable to each factor. A factor with a higher weight value would show a larger impact on drought risk and vulnerability, and a factor with a lower weight value, a smaller impact. A major effect represents the direct influence of one factor over another, while a minor effect represents an indirect influence. The study classified the major and minor effects according to their ability to deliver water to a larger portion of the study area and their roles in causing drought events. The study integrated these factors with their potential weight values by applying a weighted overlay analysis in ArcGIS. To ensure an appropriate assessment between the factors and the ranking of their respective classes, the following sources/literature were consulted, namely, Moreno-Camacho *et al*. (2019), and Singh & Devi (2022). The effects of each major and minor factor were assigned a value of 1.0 and 0.5 respectively. The proposed score for each influencing factor was calculated using equation [3].

$$\boldsymbol{MIF\ Score\ (S)} = \frac{(\boldsymbol{A}+\boldsymbol{B})}{(\sum \boldsymbol{A}+\boldsymbol{B})} \times \mathbf{100} \qquad [3]$$

Where, A is the major influencing factor and B is the minor influencing factor (see Table 6).

Table 6: MIF weights for mapping drought-prone areas

Factors	Major effect (A)	Minor effect(B)	Relative Weight (A+B)
Rainfall	1 + 1 + 1 + 1 + 1	0.5 + 0.5	6
Slope	1 + 1	0.5 + 0.5 + 0.5 + 0.5	4
Drainage Density	1 + 1 + 1	0.5 + 0.5 + 0.5	4.5
LULC	1 + 1	0.5 + 0.5 + 0.5 + 0.5 + 0.5	4.5
Soil Type	1 + 1 + 1 +1	0.5 + 0.5	5
NDWI	1	0.5 + 0.5 +0.5	2.5
NDVI	1	0.5 + 0.5	2
LST	1 + 1 + 1	0.5 + 0.5 + 0.5	4.5

Table 7: AHP and MIF ranks and weights used in the weighted overlay analysis

Factor	Rank	Severity	AHP Weight	MIF Weight
Rainfall 28.89mm	 5	 Very high	32	18
Land Surface Temperature 30.1 – 34 26.1 – 30 22.1 – 26 18.1 – 22 16 – 18	 5 4 3 2 1	 Very high High Moderate Low Very low	19	14
Slope 35.1 – 45 25.1 – 35 15.1 – 25 5.1 – 15 0 – 5	 5 4 3 2 1	 Very high High Moderate Low Very low	14	12
Drainage Density 0.456 – 1.020 0.399 – 0.456 0.239 – 0.399 0.098 – 0.239 0.002 – 0.098	 4 3 2 1 1	 High Moderate Low Very low Very low	8	14
Land Use / Land Cover Bare land Agricultural areas Areas under vegetation Built-up areas Waterbodies	 5 4 4 4 2	 Very high High High High Low	12	13
Type of soil Calcic xerosols Cambic arenosols Luvic arenosols	 4 4 3	 High High Moderate	7	15
NDVI < -0.2 - 0.2 – 0.1 0.1 – 0.3 0.3 – 0.6 0.6 – 0.9	 5 4 3 2 1	 Very high High Moderate Low Very low	4	6
NDWI < -0.5 -0.5 – -0.4 -0.4 – -0.2 -0.2 – -0.1 -0.1 – 0.2	 5 4 3 3 2	 Very high High Moderate Moderate Low	4	8

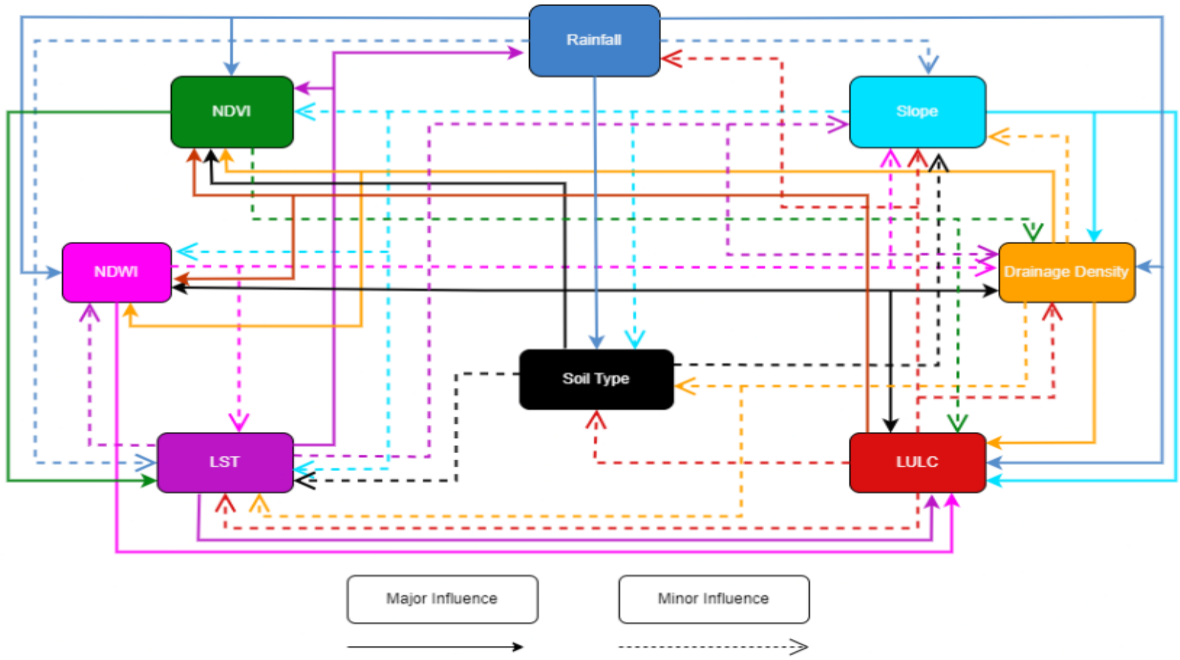

Figure 3: MIF and their interrelationships used for mapping drought-prone areas

4. Results and Discussion

The results obtained in this study are presented and discussed as follows:

4.1. Slope

Slope is a key factor in a drought assessment due to its significant influence on water runoff and soil moisture retention. It affects how water moves across the surface of the land (Magesh *et al.*, 2012). In steeply sloping areas, water tends to flow downslope at a fast rate, resulting in more runoff and less soil infiltration. This rapid drainage limits the amount of water that the soil can absorb and store, which in turn reduces soil moisture levels and increases the susceptibility of the soil to drought. On slight slopes, the soil absorbs water more readily by infiltrating into the soil rather than rapidly flowing off it (Siswanto & Sule, 2019). The study area is surrounded by a few steep slopes, but most of the terrain is level (flat) or gently sloping, where runoff is copious and the rate of infiltration is high. Therefore, steeply sloping areas are more vulnerable to drought than gently sloping areas (see Figure 4).

4.2. NDVI

The Normalised Difference Vegetation Index (NDVI) is a vegetation-derived index that measures the amount of photosynthesis occurring in plants or their green pigmentation (Singh & Devi, 2022). NDVI can be used as a response variable in semiarid and arid environments to identify and quantify drought disturbances, with low values correlating to stressed plants (Tucker & Choudhury, 1987). Increasing positive NDVI values, shown in intensifying shades of green on the images (values approaching 1), indicate increasing densities of green vegetation. NDVI values near zero and decreasing negative values approaching -1, indicate barren surfaces, such as rock and soil, where there is a dearth of vegetation. Low, but positive values, (approximately 0.2 to 0.4) represent shrub and grassland. High values may indicate temperate areas with a fair cover of vegetation (0.6 to 0.8) (Dikici, 2022). It was noted that the Rehoboth area exhibits sparse vegetation, with only a small area to the north characterised by a denser vegetation cover. The NDVI map (Figure 5) clearly shows high vulnerability to drought in the southern regions of Rehoboth, contrasting with lower vulnerability in the northern areas. As indicated by the NDVI-based analysis presented in Figure 5, the central portion of Rehoboth appears to have a moderate level of vulnerability to drought.

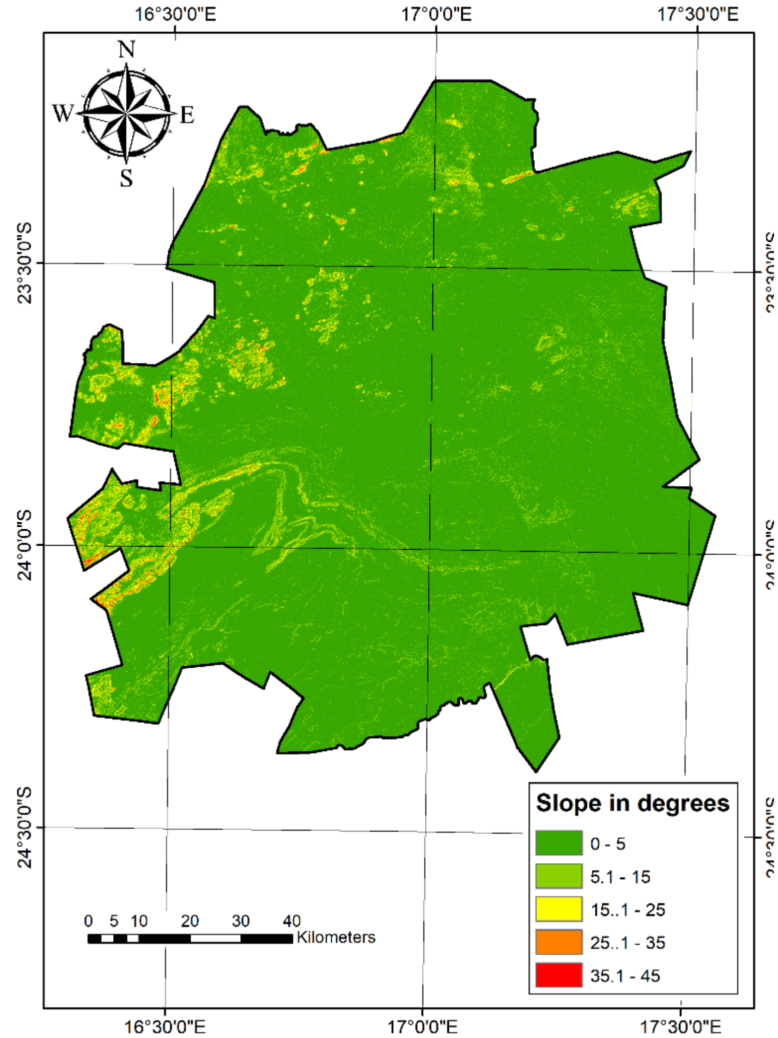

Figure 4: Slope map of Rehoboth

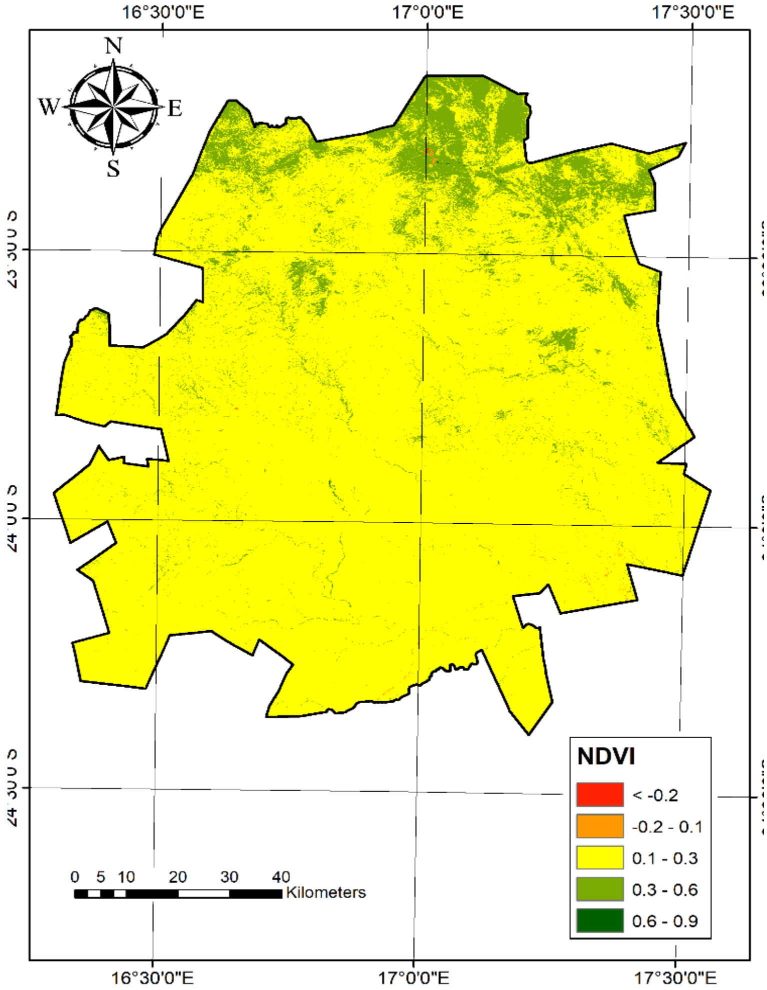

Figure 4: NDVI map of Rehoboth

4.3. Soil type

The type of soil in a region greatly influences its water recharge capacity, as well as the type of plants/crops grown and the growth tendencies of the plants in the area. As shown in Figure 6, about 3.95% of the study area is covered by Cambic arenosols, 0.158% by Calcic xerosols, and 95.79% by Luvic arenosols. Cambic Arenosols have a low water-retention capacity and a low nutrient content. Thus, they are prone to erosion and nutrient leaching. Calcic xerosols, also categorised as aridic soils[1], (have a weakly developed ochric epipedon (Fischer, 2002). Calcic xerosol soils also have a low water-retention capacity and, in the light of their aridic moisture regime, are prone to drought. On the other hand, Luvic arenosols have a mixed mineralogy, high nutrient content, and good drainage which makes them suitable for the cultivation of a wide range of agricultural products − from grain crops to fruit trees, to grapes. They have a well-developed soil profile and a sandy texture and, compared to the other two soil types, are generally better equipped to withstand drought conditions. Their

[1] Aridic soils present with an aridic moisture regime but fall short of being classified as having a hyper-aridic moisture regime.

developed soil horizons and improved water-retention capacity contribute to better moisture retention and plant resilience during droughts.

4.4. Drainage density

Drainage density is defined as the total length of the streams and rivers in an area divided by its total area (Ajayi *et al*., 2022). More practically, it is estimated by means of the expression presented in Equation [4]

$$\sum L/A \quad [4]$$

Where L= stream length, and A= area

Drainage density affects the amount of groundwater in an area (Schilling *et al*., 2015). With increasing drainage density, there is an increase in surface water runoff and infiltration into shallow aquifers. The drainage density of Rehoboth is relatively low, with only a few areas of high density. In fact, most of Rehoboth's land area is characterised by a moderate drainage density (see Figure 7).

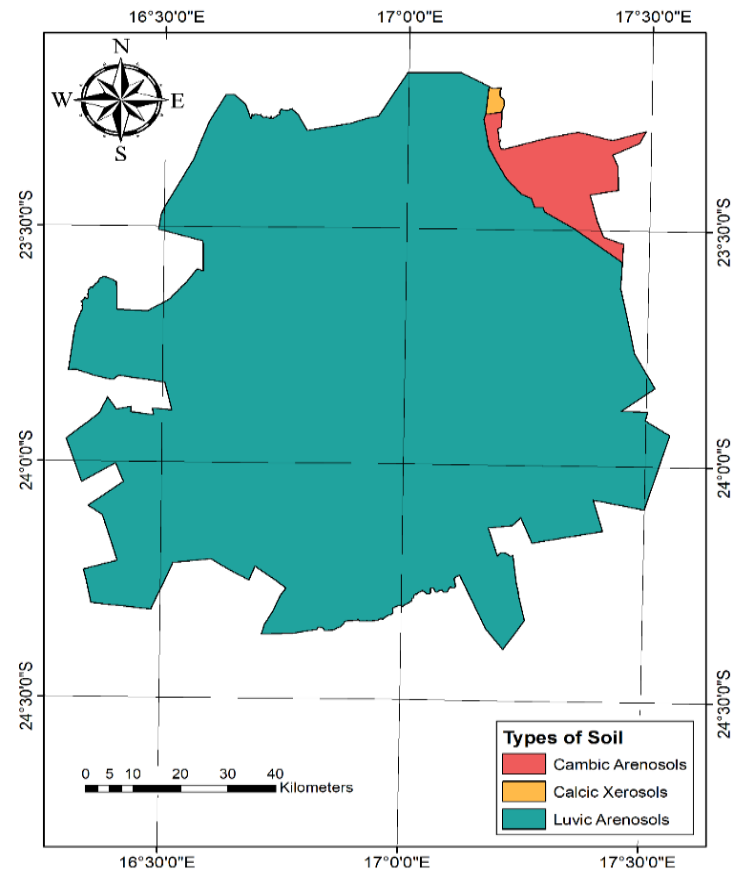

Figure 5: Map showing the soil types in the study area

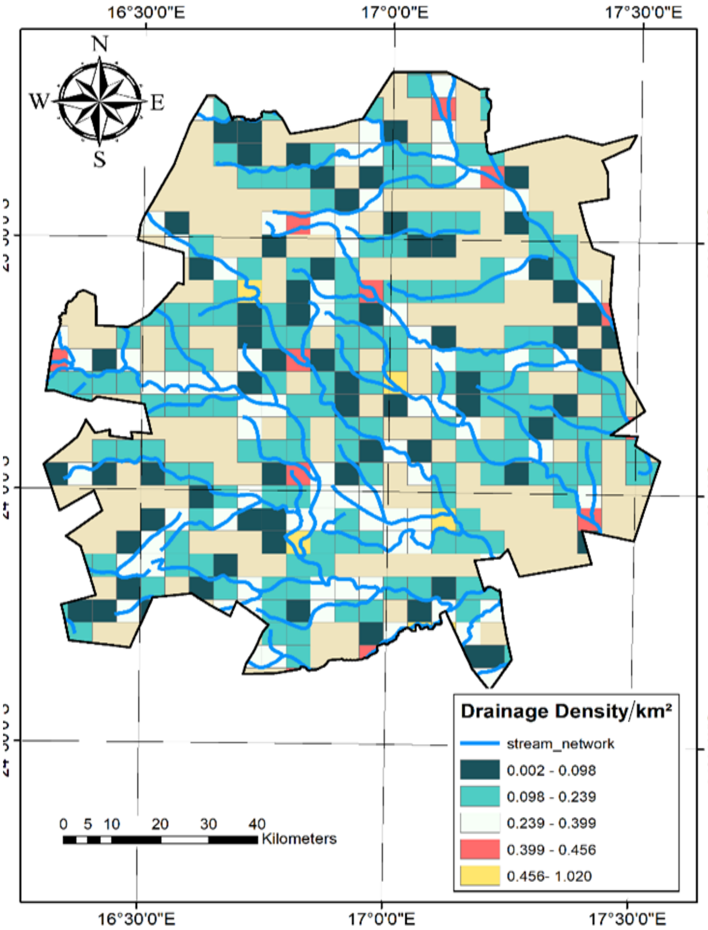

Figure 7: Drainage density map of Rehoboth

4.5. NDWI

The Normalised Difference Water Index is a satellite-derived indicator using the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) channels (Gao, 1996). It is an excellent predictor of plant water stress. Numerous studies have shown its value for drought monitoring and as an early warning drought indicator (Gu *et al*., 2008; Ceccato *et al*., 2002). The results obtained in this study show that Rehoboth has a low NDWI overall, thereby indicating that the vegetation is not under stress and that water, accommodated in water bodies such as lakes, `rivers, or wetlands, is not lacking. The only exception is Lake Oanob in the northern area of Rehoboth. The NDWI increases due south of Rehoboth, thereby indicating that the southern areas of Rehoboth have more underground water than the northern areas (see Figure 8).

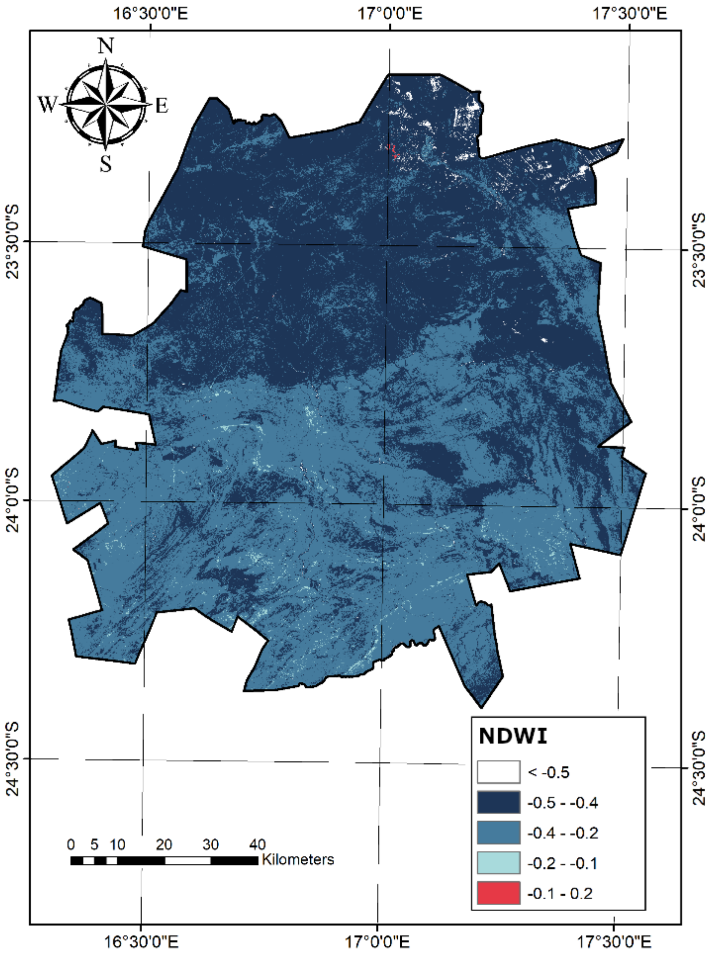

Figure 8: NDWI map of Rehoboth

4.6. Rainfall

Rainfall is a key element in determining the severity of drought. It is one of the key metrics used to gauge or measure the intensity and length of a drought event. Due to the nonlinear link between precipitation and soil moisture or runoff, less rainfall exponentially raises the danger of drought, especially in arid areas (Kim *et al*., 2023). The rainfall data used in this study was the 12-month precipitation data for Rehoboth from July 2022 to June 2023. Generally, the dry months in Namibia tend to be during the winter and autumn seasons, namely, from June to October. According to the data presented in Figure 9, December had the highest rainfall, namely, 134.2mm, with the rainfall over the other months ranging from 5.8mm to 102.5mm, thereby indicating that Rehoboth has an irregular rainfall pattern. The average annual rainfall was estimated to be 28.89mm. Rehoboth's rainfall from July 2022 to June 2023 was used to create a shapefile, which was rasterised for usage in the weighted overlay analysis.

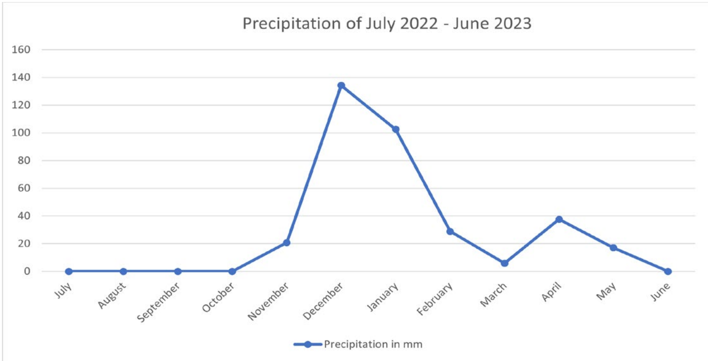

Figure 9: Rainfall chart for Rehoboth

4.7. Land surface temperature

Land surface temperature (LST) is an important climatic parameter involved in drought assessments. It is defined as the temperature felt when touching the ground surface by hand and plays a significant role in understanding climate change (Rajeshwari & Mani, 2014; Bhattacharya & Dadhwal, 2003; & Ajayi *et al*., 2023). Drought is characterised by a lack of moisture in the soil and vegetation, thereby leading to reduced evapotranspiration and causing surface temperatures to increase. Thus, one can easily observe areas lacking in moisture. The climatic conditions in the study area are relatively hot, with temperatures ranging from 22°C to 33°C to the south, and lower temperatures prevailing in the northern areas. Thus, unlike the less temperate regions, temperate areas are more susceptible to drought. The LST map of the study area is presented in Figure 10.

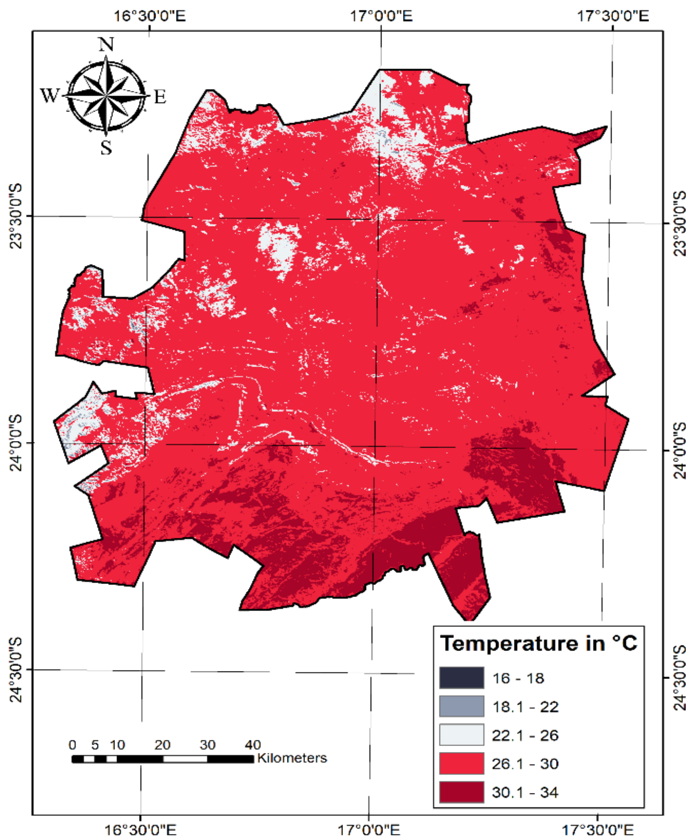

Figure 10: LST map of the study area

4.8. Land use / Land cover

Different types of land use / land cover have different thermal characteristics. Therefore, variations in land surface temperature influence the evapotranspiration rate of the different types of land use / land cover. Areas under vegetation, such as woodland and farmlands, typically experience higher evapotranspiration rates than built-up areas or barren land. In fact, high evapotranspiration rates have the potential to aggravate drought situations in that they dry up the moisture in the soil. The types of land use / land cover also impact on the way in which water interacts with the land surface, as in the case of surface runoff and infiltration. Built-up areas with extensive impervious surfaces can lead to increased surface runoff and reduced infiltration of water into the soil. These two processes reduce the amount of water available for groundwater recharge and may lead to drought. The land use / land cover map for Rehoboth (Figure 11) shows that most of the study area is classified as agricultural land or built-up, while bare land, areas under vegetation, and waterbodies make up only a small portion of the study area. Due to the respective variations in their evaporation and surface runoff rates, agricultural, vegetated and bare lands are more susceptible to drought, built-up areas are moderately affected, while waterbodies are least susceptible.

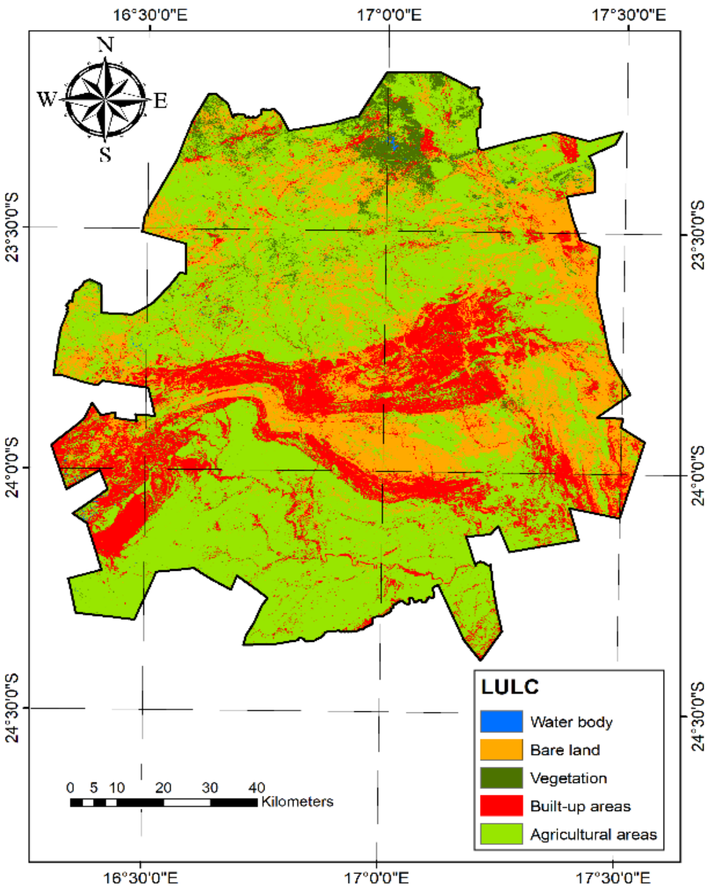

Figure 11: LULC of the study area

4.9. Drought severity modelling

The drought zone maps showing the drought risk assessment for Rehoboth that were compiled using the AHP and MIF methods are presented in Figures 12 and 13, respectively. They differentiate the study area into three drought risk categories, namely, slight, moderate, and severe. The AHP method of classification, as depicted in Figure 12, shows that the areas of slight drought risk in Rehoboth are widespread, with moderate risk zones concentrated in the central region, and severe risk areas in the northern portion of the study area. Settlements such as Rietoog, Klein Aub, Tsumis, Kauchas, and Karanas are only slightly at risk of drought, while Kobos, Groendraai, Witkop, Lammerwater, and Blokwater fall into the moderate risk category, with only the Schlip and Omomas settlements facing severe risk. Comparatively, the MIF method yields similar findings to those of AHP, but with minor discrepancies in the distribution of risk classes, particularly in the severe risk areas, where the risk severity is lower than that shown in the AHP classification. In terms of the MIF method, settlements such as Rietoog, Klein Aub, Tsumis, Kauchas, and Karanas face a slight drought risk, with the moderate risk category including settlements such as Kobos, Groendraai, Witkop, Lammerwater, and Blokwater, and only Schlip facing severe drought risk.

The tabulated results in Tables 8 and 9 further demonstrate the consistency between the two methods, with the percentages of the drought-affected areas aligning closely. AHP indicates 87.09% slight risk, 12.24% moderate risk, and 0.68% severe risk, while MIF shows 87.08% slight risk, 12.8% moderate risk, and 0.12% severe risk. This convergence reinforces the reliability of both methodologies.

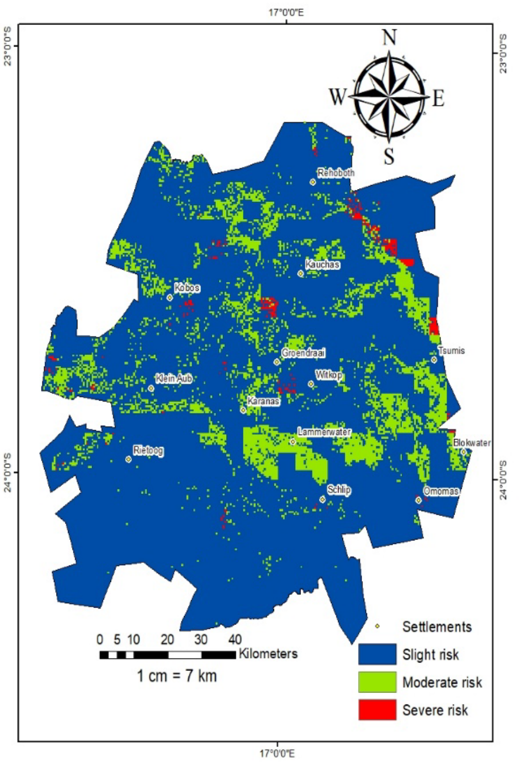

Figure 12: Drought-prone areas according to the AHP method

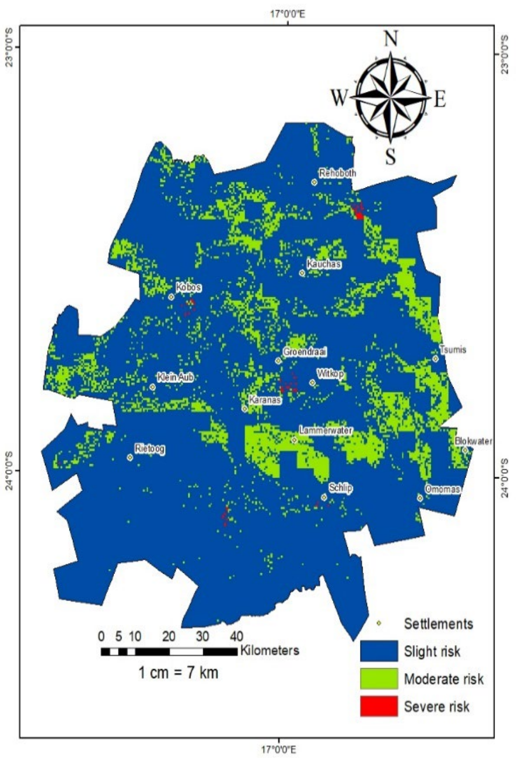

Figure 13: Drought-prone areas according to the MIF method

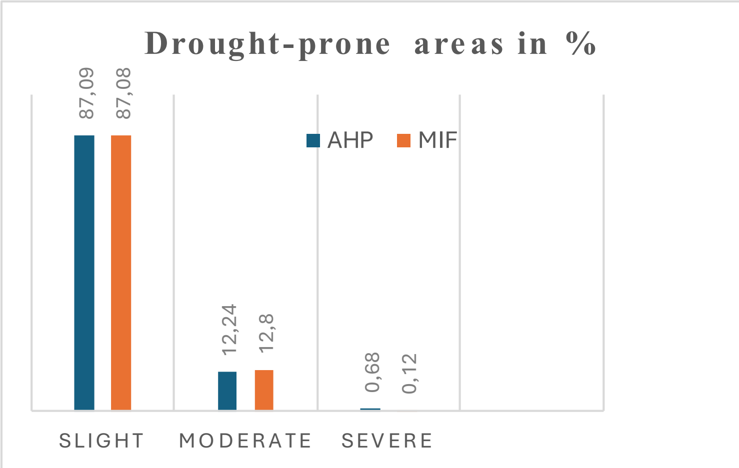

Figure 14 Percentage distribution of drought risk areas in the study area based on AHP and MIF

Table 8: Areas affected (AHP method)

Drought risk	Area	% of area
Slight risk	10150.84122km^2	87.09%
Moderate risk	1426.133246km^2	12.24%
Severe risk	78.725533km^2	0.68%

Table 9: Areas affected (MIF method)

Drought risk	Area	% of area
Slight risk	10149.8209km^2	87.08%
Moderate risk	1491.5310km^2	12.8%
Severe risk	14.3480km^2	0.12%

5. Conclusion

In this study, we applied GIS and Remote Sensing techniques to map and assess drought-prone areas in Rehoboth, a town located in the Hardap region of Namibia. We considered eight driving factors of drought, namely slope, land surface temperature (LST), land use/land cover (LULC), the Normalised Difference Water Index (NDWI), the Normalised Difference Vegetation Index (NDVI), rainfall, soil type, and drainage density, resulting in the production of a thematic map for each factor. Using the Analytic Hierarchy Process (AHP) method, we assigned accurate weights to each factor while ensuring a Consistency Ratio (C.R) of less than 10%. Additionally, the Multi-Influencing Factor (MIF) method helped us to identify major and minor influences contributing to water scarcity in the study area. Subsequently, we performed a weighted overlay to merge these factors, incorporating weights determined by both the AHP and MIF methods, thereby creating comparative maps showing the pertinent drought-prone areas. The resulting maps were then classified into three classes: slight drought risk, moderate drought risk, and severe drought risk. In the AHP classification, 87.09% of the area was deemed slightly at risk, 12.24% moderately at risk, and 0.68% severely at risk. In contrast, the MIF classification showed 87.08% of the area at slight risk, 12.80% at moderate risk, and 0.12% at severe risk.

The integration of advanced multi-criteria decision-making tools, such as the AHP and MIF methodologies, and a weighted overlay analysis, provides a transparent and replicable framework for drought risk assessment in arid and semi-arid regions. This methodological approach enables stakeholders to prioritise drought indicators based on both quantitative evidence and expert knowledge, thereby supporting more informed and adaptive resource management decisions. By standardising and weighting the key drought parameters, namely, rainfall, slope, drainage density, soil type, land surface temperature, land use / land cover, NDVI, and NDWI, it is possible to provide a practical tool that can be readily adapted to different geographic and climatic contexts, thereby supporting regional planning and disaster preparedness. With regard to policymakers and land managers, the outputs of the study can guide targeted interventions, such as identifying high-risk zones for drought mitigation investments, optimising water resource allocation, and informing land use planning to enhance resilience. The spatially explicit maps generated can also facilitate communication and engagement with local communities, making scientific findings more accessible to non-technical stakeholders and thus promoting their required action. This is particularly relevant as climate variability intensifies, thereby increasing the frequency and severity of drought events and amplifying their socioeconomic impacts.

This study contributes to the field of Environmental Decision Science by demonstrating how the integration of multiple data sources and expert judgment can improve the robustness of drought vulnerability assessments. It also highlights the importance of considering spatial interdependencies and the dynamic interactions between natural and anthropogenic factors in environmental risk analysis, the implications of which can be extended to future research and policy. The methodological framework presented in this study can be replicated for other environmental hazards, such as floods or land degradation, and to promote interdisciplinary applications and adaptive management or mitigation strategies. This approach encourages ongoing monitoring and iterative refinement as new data and technologies become available, thereby supporting evidence-based policy and adaptive management in the face of environmental change.

Ethical Compliance

The authors declare that this study was conducted in compliance with all known ethical standards.

Availability of supporting data

Data used for this study will be provided by the corresponding author upon reasonable request.

Declaration of competing interests

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

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Authors' contributions

Both authors contributed to the conception and design of this study. Material preparation, data collection, analysis, and validation were performed by R.T.B. The first draft of the manuscript was written by R.T.B. and substantially revised by O.G.A. Both authors reviewed and approved the manuscript.

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