



SPATIAL ANALYSIS OF DROUGHT AND WATER CARRYING CAPACITY IN THE DYNAMIC DEVELOPMENT AREA OF ACEH BESAR REGENCY BASED ON REMOTE SENSING

Cut Dilla Amalia Fonna¹, Mirza Irwansyah¹, Fahmi Aulia^{*}

¹Department of Architecture and Planning, Engineering Faculty, Universitas Syiah Kuala, Banda Aceh, Indonesia

*Correspondence: fahmiaulia@usk.ac.id

Article Information

• Received: 20/06/2025

• Accepted: 25/09/2026

• Available Online: 30/09/2026

ABSTRACT

Drought is conventionally diagnosed through rainfall deficit, yet in humid tropical regions the land surface can be under severe moisture stress while precipitation remains close to its long-term average. This study analyzes that divergences and its consequences for water carrying capacity across Lhoknga, Peukan Bada, and Darul Imarah Districts, Aceh Besar Regency, covering 14,613.97 hectares. Landsat 8 OLI imagery and CHIRPS precipitation data were processed in Google Earth Engine and ArcGIS. Meteorological drought was assessed using the Standardized Precipitation Index (SPI) and vegetation drought was using the Normalized Difference Drought Index (NDDI), while water carrying capacity was derived from the balance between water availability and demand against a threshold of 1,600 m³/capita/year. The two indices diverge sharply. SPI indicates near-normal precipitation across 14,604.67 ha, or almost the entire study area, where NDDI classifies 13,613.74 hectares (93%) experiencing the least moderate drought (NDDI > 0.3). Water deficit affects 2,454.68 hectares (17%), concentrated in densely populated areas such as Darul Imarah. Geographically Weighted Regression (GWR) revealed Local R² values ranging from 0.02 to 0.304, with the highest concentration in southern Darul Imarah but falling below 0.15 across most of Lhoknga and Peukan Bada. Surface drought therefore accounts for at most one third of the spatial variation in water carrying capacity, and substantially less in most locations. The residual variation points to mechanism that index cannot observe: karst hydrology with high infiltration but negligible storage and the horizontal expansion of built-up area long Banda Aceh boundary. This finding carries a practical implication for spatial planning, namely that rainfall-based drought monitoring will systematically underestimate water stress in karst-dominated peri-urban territory.

Keywords: Drought, Water Carrying Capacity, SPI, NDDI, GWR, Karst

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1. INTRODUCTION

Drought is a recurrent feature of the natural climate cycle, characterized by prolonged dry periods that occur across a wide range of climatic zones (WMO, 2020). Its consequences extend well beyond water availability, reaching into livelihoods, public health and the productivity of land. Crausbay et al. (2017) define ecological drought as an episodic water shortage that drives ecosystems past their vulnerability thresholds, disrupts ecosystem services, and triggers responses in natural systems, human systems or both (Crausbay et al., 2017). In Indonesia, this phenomenon is becoming more frequent due to a combination of climate change and environmental degradation. Vulnerability to drought has increased significantly as a consequence of global climate change, rapid population growth, and increased pressure on water resources due to various human needs. Water is not only required for consumption purposes such as drinking and sanitation, but is also critical in the industrial sector as well as agricultural production. Limited water supply due to these factors has made drought an increasingly complex issue (Eslamian & Eslamian, 2017).

Drought is conventionally classified into four types: meteorological, agricultural, hydrological, and socio-economic drought, each corresponding to a different stage in the propagation of a precipitation deficit

through the hydrological cycle and into human systems (Wilhite & Glantz, 1985; WMO & GWP, 2016). This Study is positioned at the intersection of the first two. It uses a precipitation-based indicator to capture the meteorological signal and a vegetation-moisture indicator to capture the agricultural and ecological response, on the premise that the relationship between the two is not a given and that where they part company something diagnostically useful is revealed.

Seasonal drought bears heavily on water availability in areas undergoing rapid settlement. According to Aceh Disaster Management Agency (Badan Penanggulangan Bencana Aceh - BPBA), the prolonged dry season has triggered drought in Aceh Province. This makes drought the second most frequent disaster in Aceh (Chairani et al., 2022). One of the areas vulnerable to such disasters is Aceh Besar District. Based on data from the National Disaster Management Agency (Badan Nasional Penanggulangan Bencana - BNPB), Aceh Besar District obtained a drought disaster risk index score of 11.54, which is included in the moderate risk category (BNPB, 2020). The drought phenomenon that hit Aceh Besar District showed a higher vulnerability in certain areas, such as Lhoknga, Peukan Bada, and Darul Imarah sub-districts. These three sub-districts often experience a deficit in clean water availability during the long dry season, which has an impact on agricultural activities, household water availability, and decreased land productivity.

This is directly related to the concept of water carrying capacity, which is the ability of an area to provide sufficient water for actual needs without damaging environmental sustainability. The relationship between drought and reduced water carrying capacity has been identified, but not many have described the relationship spatially, especially in areas with high disaster vulnerability. Therefore, an approach is needed that is able to measure drought spatially and relate it directly to water carrying capacity. The indicators used are Normalized Difference Drought Index (NDDI) and Standardized Precipitation Index (SPI). A high NDDI value signals severe drought, since it reflects a simultaneous decline in vegetation greenness and surface moisture (Artikanur et al., 2022). NDDI, however, only describes the response of the land surface; it says nothing about whether that response was driven by a rainfall deficit. This is why a second, precipitation-based indicator is required. The Standardized Precipitation Index (SPI) expresses rainfall over a given accumulation period as a standardized departure from its long-term climatological mean, which makes it possible to distinguish areas under genuine meteorological deficit from areas that are dry despite normal rainfall (McKee et al., 1993). Used together, the two indices separate the climatic driver from the surface condition and it is precisely the divergence between them that this study treats as diagnostically important.

Several standardized drought indices are available, and the choice among them carries analytical consequences. The Palmer Drought Severity Index incorporates a soil water balance but requires calibration parameters that are rarely available at sub-district resolution in Indonesia. The Standardized Precipitation Evapotranspiration Index (SPEI) extends SPI by subtracting potential evapotranspiration from precipitation, and comparative studies have shown that SPEI is generally more sensitive than SPI in regions where warming has intensified atmospheric water demand (Vicente-Serrano et al., 2010; Arra & Şişman, 2024). SPI was nevertheless adopted here for two reasons. First, its input requirement is minimal, which allows it to be computed consistently from a single gridded precipitation product (CHIRPS) across the entire study area without introducing the additional uncertainty that temperature-based evapotranspiration estimates would carry in a data-sparse tropical setting (Funk et al., 2015). Second, and more importantly for the argument developed in this paper, SPI isolates the precipitation signal alone. Because the analysis aims to test whether vegetative drought in the study area can be attributed to rainfall deficit, an index that deliberately excludes evaporative demand functions as a conservative control: if SPI indicates normal precipitation while NDDI indicates moisture stress, the discrepancy cannot be explained by rainfall and must be sought in land surface and hydrogeological conditions. The limitations that this choice imposes are addressed in the concluding section.

Drought index processing is done by remote sensing, which can provide accurate and up-to-date information to support spatial analysis in planning activities and natural resource management. Data obtained through satellites has a number of advantages, such as relatively low cost, the ability to record the same location periodically, the use of various wavelengths to minimize atmospheric disturbances, wide coverage of areas to remote areas, and digital data form. In addition, the combination of various spectral

channels allows the data to be further processed for various purposes, such as administrative mapping, land cover mapping, and other applications (Niagara et al., 2020). Processing is carried out based on *Google Earth Engine* (GEE), which is a geospatial data analysis platform that utilizes Google's data repository and is supported by cloud-based computing technology (Fikri et al., 2021).

Water carrying capacity is the ability of water resources to meet the needs of human life and the environment, both as benefits and potential risks (Ernamaiyanti & Yunanda, 2021). This concept comes from biology and refers to the balance between water availability and the needs that must be met. Water carrying capacity is calculated based on the ratio between the amount of water available and the community's water needs (Santoso, 2015). Processing of water carrying capacity is carried out using a variety of scale grid methods that can describe a phenomenon with a pattern that does not change or change monotonically in scale by utilizing information that refers to a range of scales simultaneously (Norvyani & Taradini, 2016). Geographically Weighted Regression (GWR) is a regression method that allows model parameters to vary spatially by building a local regression model for each observation location. The relationship between drought and water carrying capacity is unlikely to be uniform across space. Water availability is shaped by rainfall, but also by land cover, population concentration, and subsurface geology, and these vary sharply over short distances in the study area: karst terrain in the south, coastal plains in the west, and peri-urban settlement expansion in the east. A single global regression coefficient would average these contrasts away and report a weak association without revealing where, or why, the association is weak. An estimator that allows the coefficient itself to vary by location is therefore required. Geographically Weighted Regression (GWR) is a local regression technique that estimates a separate set of parameters for every observation point, using a distance-decay weighting scheme, and thereby makes spatial non-stationarity in the relationship directly observable rather than treating it as residual noise (Brunsdon et al., 1996; Fotheringham et al., 2002). This allows the analysis of the relationship between dependent and independent variables that may change depending on geographic location. This model is particularly useful in identifying and understanding spatial variation in data, which cannot be captured by global regression models (Caraka & Yasin, 2017).

Based on this background, this study aims to identify the impact of the distribution pattern of drought-prone areas on water carrying capacity in Lhoknga, Peukan Bada, and Darul Imarah sub-districts. The results of this study are expected to provide accurate scientific information for local governments and policy makers in formulating drought adaptation and mitigation strategies, as well as strengthening community capacity in dealing with water crises in a sustainable manner.

2. DATA AND METHODS

2.1. Study Location

This study was conducted in three sub-districts located in Aceh Besar District, namely Lhoknga, Peukan Bada, and Darul Imarah based on Figure 1. These three areas were selected because they have characteristics that are vulnerable to drought and show significant pressure on the water carrying capacity of settlements, especially in the dry season. The study area covers a total area of 14,613.97 hectares with the following administrative boundaries. The study area comprises three contiguous sub-districts in the northwestern part of Aceh Besar Regency, covering 14,613.97 ha in total and bounded by the Malacca Strait and Banda Aceh City to the north, the Indian Ocean to the west, and the regency interior to the south and east (Figure 1).

The study area has a diverse demographic character and plays an important role in the socio-economic development of Aceh Besar District. Based on data from the Badan Pusat Statistik (BPS), Lhoknga Subdistrict covers an area of approximately 8,644.15 hectares and consists of 28 villages, with an estimated population of approximately 17,900 people and a density of approximately 204 people per square kilometer. Meanwhile, Peukan Bada Subdistrict, which has an area of 3,573.24 hectares, serves as a buffer zone for the city of Banda Aceh.



Figure 1. Research Location

This area is inhabited by around 27,100 people, with a population density of 748 people per square kilometer. Darul Imarah Subdistrict, with an area of 2,396.58 hectares, has the highest population density of the three, at more than 2,385 people per square kilometer, with a total population of around 58,100. These three sub-districts, which reflect densely populated residential areas and have direct access to the provincial government center, face significant challenges in water management, especially when facing the long dry season.

2.2. Research Data

The research used a spatial-based quantitative approach by utilizing remote sensing technology and geographic information systems (GIS). The main tools used in the analysis process are the Google Earth Engine (GEE) platform for satellite image processing, and ArcGIS software for spatial mapping. The data used in this research is secondary data, which is data obtained from agencies/companies that are published to other parties (Syahza, 2021). The data includes Landsat 8 OLI satellite image data, CHIRPS rainfall data, shapefiles of boundaries and road networks from the Geospatial Information Agency (Badan Informasi Geospasial - BIG), and population data from the Central Bureau of Statistics (Badan Pusat Statistik - BPS). The datasets used, their sources, and the outputs derived from each are summarized in Table 1.

Table 1. Data Requirement

Goals	Required Data	Data Type	Data Source	Output
Determine overall administrative boundaries	Shapefile of Aceh	Secondary	Geospatial Information Agency	Research location map
	Besar District			
	Administrative Boundaries			
	Landsat 8	Secondary	Google Earth Engine	

Goals	Required Data	Data Type	Data Source	Output
Identifying the distribution pattern of drought-prone areas in Lhoknga, Peukan Bada, and Darul Imarah sub-districts	CHIRPS Rainfall Data	Secondary	Google Earth Engine	Map of drought-prone distribution patterns based on SPI and NDDI
	Vegetation Data (NDVI)	Secondary	Google Earth Engine	
	Data NDWI	Secondary	Google Earth Engine	
Identifying the water carrying capacity of settlements in Lhoknga, Peukan Bada, and Darul Imarah sub-districts	CHIRPS Rainfall Data	Secondary	Google Earth Engine	Water carrying capacity map
	Landcover data	Secondary	Google Earth Engine	
	SHP Road Boundary	Secondary	Badan Informasi Geospasial	
	Population data	Secondary	BPS	

2.3. Analysis Method

Three analytical approaches are combined: digital interpretation of satellite imagery to derive drought indices, a multi-scale grid system to compute water carrying capacity, and Geographically Weighted Regression to model the spatial relationship between them. Each is described below, and the overall research sequence is presented in Figure 6.

Digital image interpretation is carried out by examining satellite imagery to identify objects and phenomena on the earth's surface, in this case to detect drought-prone areas. Two indices are derived. The Normalized Difference Drought Index (NDDI) combines the Normalized Difference Vegetation Index (NDVI), which represents vegetation condition, with the Normalized Difference Water Index (NDWI), which reflects moisture content in soil and canopy. The Standardized Precipitation Index (SPI) expresses accumulated rainfall as a standardized departure from its long-term climatological mean. The formulas for NDDI and SPI are as follows:

$$NDDI = \frac{(NDVI - NDWI)}{(NDVI + NDWI)} \quad \text{Equation (1)}$$

$$SPI = \frac{X_{ik} - \bar{X}_1}{\sigma_i} \quad \text{Equation (2)}$$

The wider the gap between NDVI and NDWI, the higher the NDDI value, indicating vegetation that appears green but is under moisture stress. The index was originally developed for grassland drought assessment in the central Great Plains (Gu et al., 2007) and has since been adapted for semi-arid and tropical settings (Artikanur et al., 2022; Patil et al., 2024). NDDI was derived here from Landsat 8 OLI Level 2 Tier 1 surface reflectance imagery accessed through Google Earth Engine (Gorelick et al., 2017), covering January to December 2024 with a maximum scene cloud cover of 30%. Images were cloud- and shadow-masked using the pixel quality assessment band, then reduced to an annual median composite to suppress residual atmospheric noise and produce a stable representation of vegetation and moisture conditions. NDVI and NDWI were computed from the composite and combined following Equation (1). Resulting values were classified into six classes following the thresholds proposed by Patil et al. (2024), presented in Table 2. The complete processing sequence is shown in Figure 2. Surface reflectance imagery accessed through Google Earth Engine (Gorelick et al., 2017), covering January to December 2024 with a maximum scene cloud cover of 30%. Images were cloud- and shadow-masked using the pixel quality assessment band, then reduced to an annual median composite to suppress residual atmospheric noise and produce a stable representation of vegetation and moisture conditions. NDVI and NDWI were computed from the composite and combined following Equation (1). Resulting values were classified into six classes following the thresholds proposed by Patil et al. (2024), presented in Table 2. The complete processing sequence is shown in Figure 2.

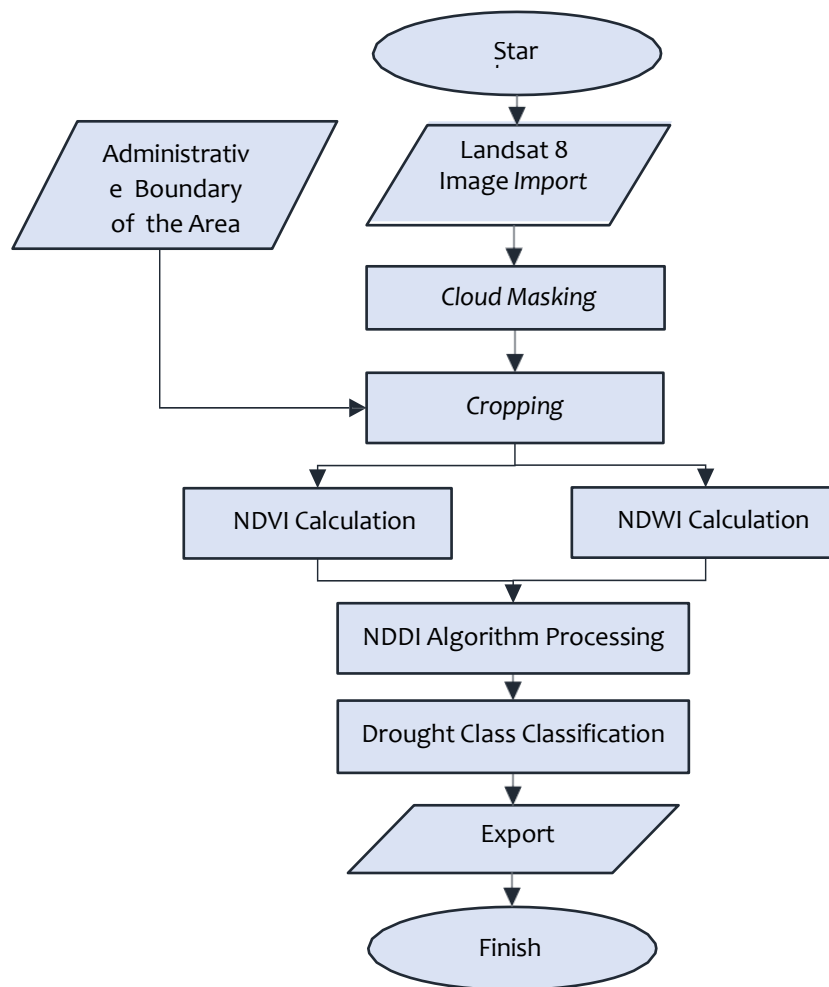


Figure 2. NDDI Digital Image Interpretation Flowchart

Table 2. NDDI Classification Thresholds

NDDI Value	Classification
< -1	Water Body
-1 - 0.2	No Drought
0.2 - 0.3	Mild Drought
0.3 - 0.4	Moderate Drought
0.4 - 0.5	Severe Drought
0.5 - 1.0	Extreme Drought

Source: Patil et al. (2024)

Negative SPI values indicate rainfall below normal and therefore meteorological drought, while positive values indicate rainfall above the long-term average. Because the index is standardized, values remain comparable across regions and periods, which is the property that makes it useful here. SPI was computed from CHIRPS v2.0 daily precipitation (Funk et al., 2015), aggregated to monthly totals over the period 1994 to 2024. A 12-month accumulation window (SPI-12) was applied to capture drought at the annual hydrological scale, with a gamma distribution fitted to the record at each grid cell and subsequently transformed to a standard normal variate. SPI values for the reference year were then classified following WMO (2012), presented in Table 3. The processing sequence is shown in Figure 3.

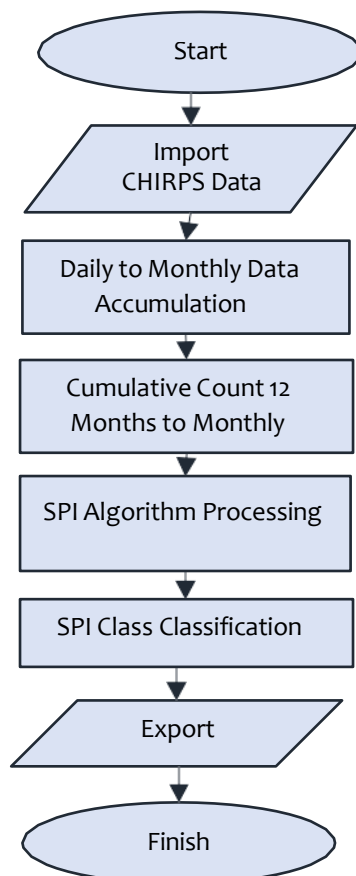


Figure 3. SPI Digital Image Interpretation Flowchart

Table 33. SPI Classification Thresholds

SPI Value	Classification
>2.0	Extremely wet
1.5 – 1.99	Very wet
1.0 – 1.49	Moderately wet
-0.99 – 0.99	Near normal
-1.0 – -1.49	Moderately dry
-1.5 – -1.99	Severely dry
<-2.0	Extremely dry

Source: WMO (2012)

The next step is the application of the multi-scale grid system method. In this method, the study area was divided into a 5" x 5" resolution grid to map spatial information related to water carrying capacity. A grid system is a two-dimensional structure that organizes an area into contiguous units of unique cells, where each cell has its own identifier used for spatial analysis. The multiscale approach is utilized to describe phenomena that are fixed or gradually changing at various scales of analysis. One important component of this method is the population grid, which is used to estimate population distribution and density in spatial detail. This data is then combined with information on water availability and demand to calculate the water carrying capacity of each grid unit. The results of this processing illustrate the balance between water supply and demand and identify areas of surplus or deficit, which are then compared against the drought-prone areas mapped above. The same 5 by 5 arc-second resolution is used throughout, so that grid-level results remain directly comparable with the index rasters. The processing sequence is shown in Figure 4.

$$SA = 10 \times C \times R \times A \quad \text{Equation (3)}$$

$$DA = N \times KHLA \quad \text{Equation (4)}$$

$$DDA = SA - DA \quad \text{Equation (5)}$$

In the calculation of water carrying capacity, two main components are used: water availability (SA) and water demand (DA). Water availability is calculated based on area, average annual rainfall, and weighted runoff coefficients obtained from different types of land use. This coefficient indicates what proportion of rainwater becomes surface runoff. In contrast, water demand is calculated based on the total population and the standard minimum water requirement per capita per year, which includes domestic as well as food purposes. The difference between water availability and water demand yields the water carrying capacity (DDA) value, where a positive value indicates sufficiency and a negative value indicates pressure on water resources. The threshold applied here is 1,600 m³ per capita per year, following Regulation of the Minister of Environment No. 17/2009, which is somewhat stricter than the 1,700 m³ figure conventionally used internationally (Falkenmark et al., 1989).

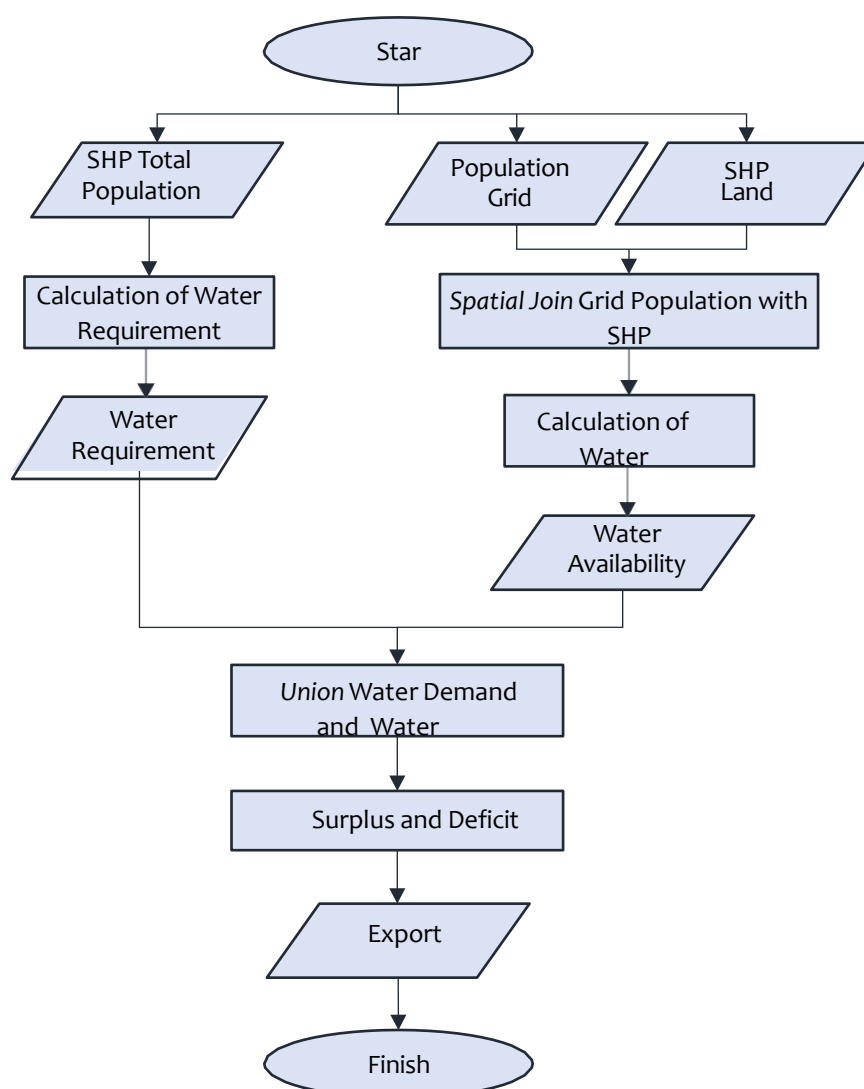


Figure 4. Water Carrying Capacity Processing Flowchart

Finally, to examine the relationship between drought and water carrying capacity spatially, this study utilizes the Geographically Weighted Regression (GWR) method. GWR allows the analysis of the relationship

between variables by considering local variations in each location. In this study, the independent variable (X) is the average NDDI value per village, which reflects the level of drought based on Landsat satellite image data. Meanwhile, the dependent variable (Y) is the value of settlement water carrying capacity per village, which is calculated from the ratio between water availability and water demand, based on population and potential water resources. With the GWR approach, the spatial relationship between the two variables can be analyzed in more depth at the local level, providing a more accurate picture of the dynamics of drought vulnerability and water carrying capacity in the study area, particularly in Lhoknga, Peukan Bada, and Darul Imarah sub-districts. The general form of the GWR model can be expressed as follows:

$$y_i = \beta_0(u_0, v_0) + \sum \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, i=1,2,\dots,n \quad \text{Equation (6)}$$

In analyzing the spatial relationship between these variables, the Geographically Weighted Regression (GWR) method is used. This model allows each location to have different regression parameters, thus capturing local variations in the relationship between variables. In the GWR equation, the response value at each observation point is influenced by the value of the predictor variables and the coefficients are calculated based on the geographical coordinates of each location. This approach produces a spatially adaptive model and allows for a more accurate interpretation of the spatially heterogeneous pattern of relationships between variables.

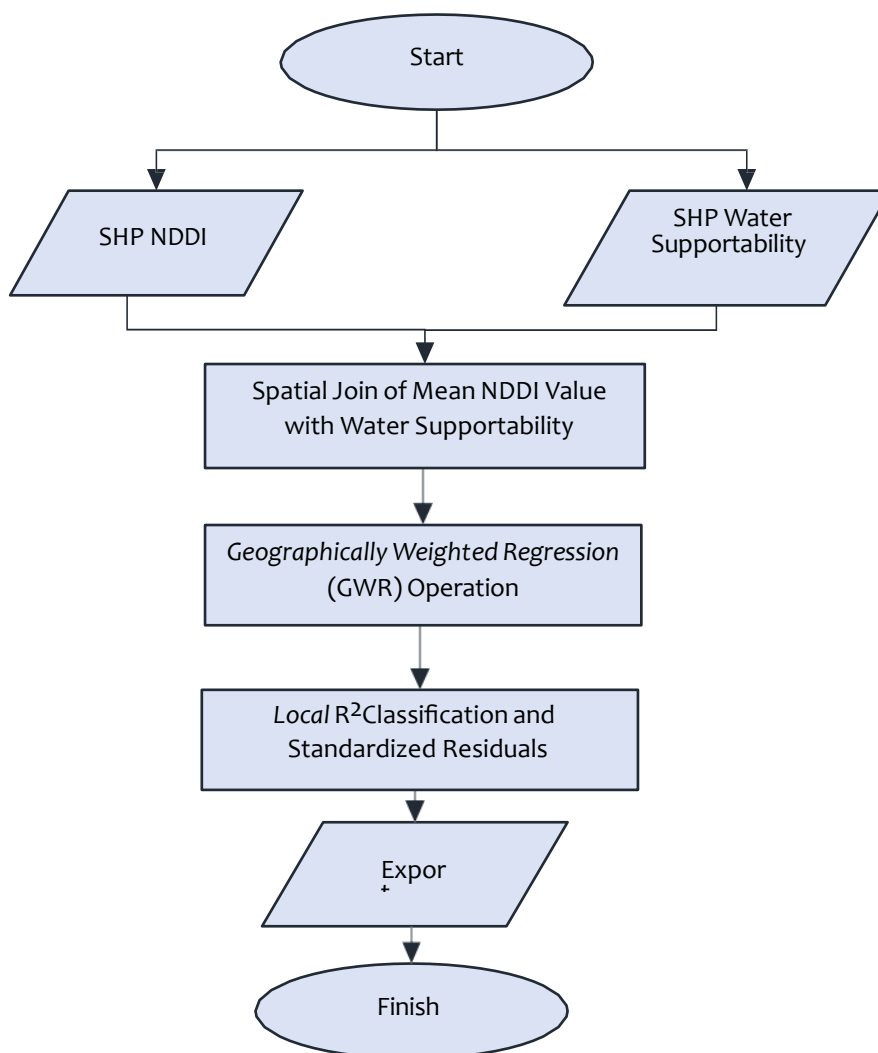


Figure 5. Flowchart Geographically Weighted Regression (GWR)

Both variables were aggregated to the village level ($n = [\text{jumlah desa}]$) using zonal means, and the model was estimated in ArcGIS with a [kernel: fixed atau adaptive; Gaussian atau bi-square] weighting scheme, with bandwidth selected by [AICc atau cross-validation]. Because the two variables were originally derived at different spatial resolutions, grid cells for carrying capacity and image pixels for NDDI, aggregation to a common village-level unit introduces sensitivity to the Modifiable Areal Unit Problem. Results should accordingly be read at the village scale and not extrapolated to finer resolutions. The processing sequence is shown in Figure 5.

Based on the indicators and methods previously described, it is necessary to develop a systematic research flow to ensure that the linkages between the stages of analysis can run coherently and purposefully. This flow describes the operational stages from data collection, processing, to spatial analysis and interpretation of results. The preparation of the research flow also aims to clarify the logic of the process in linking drought conditions with water carrying capacity, as well as supporting the modeling of spatial relationships between the variables studied. The full sequence, linking data acquisition through index derivation to spatial modelling and interpretation, is presented in Figure 6.

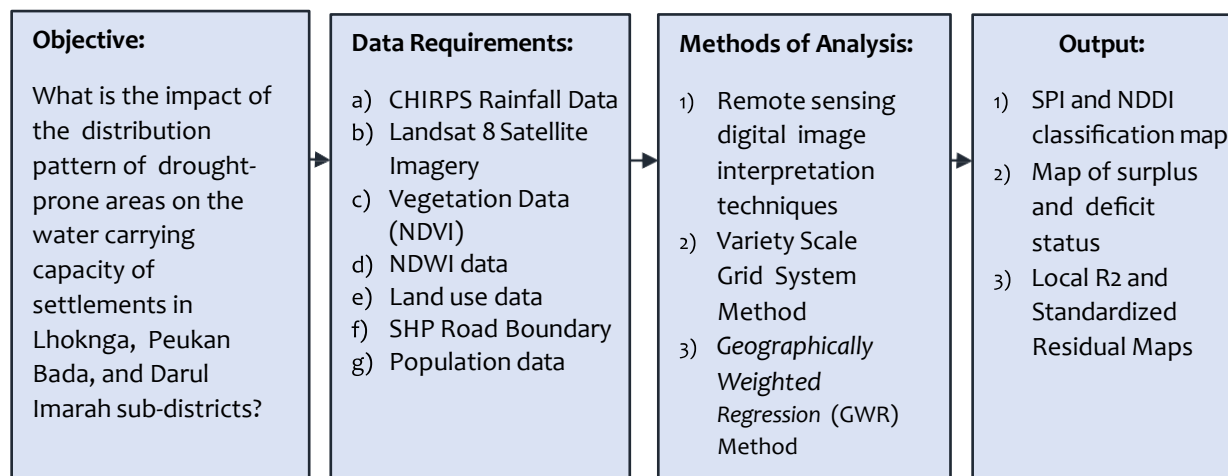


Figure 6. Research Flow

3. RESULTS AND DISCUSSION

This section proceeds in five steps. It first establishes the distribution of vegetative drought and then of meteorological drought, before examining the divergence between them, which is the study's principal empirical finding. It then maps water carrying capacity and models its spatial relationship with drought, closing with an interpretation of what the model does not explain.

3.1. Vegetative Drought Distribution Based on NDDI

NDDI classification across the study area is presented in Figure 7, with class areas given in Table 4. The distribution is heavily weighted toward the dry end of the scale. Moderate drought alone accounts for 7,748.35 ha, or 53.0% of the study area, while severe and extreme drought together cover a further 5,865.39 ha, or 40.1%. Taken together, 13,613.74 ha, equivalent to 93.2% of the total, register at least moderate drought, while areas classified as showing no drought amount to just 25.68 ha. The pattern is not uniform across the three sub-districts. Extreme drought, shown in bright red where NDDI approaches unity, concentrates in two distinct settings: the southern portion of Lhoknga, where limestone outcrops and active quarrying have left extensive areas of exposed rock and bare soil, and the eastern margin of Darul Imarah along the boundary with Banda Aceh City, where built-up surface has displaced vegetation across a contiguous zone. Peukan Bada occupies an intermediate position, dominated by the moderate class, with lower values confined to the coastal strip where remnant vegetation persists. That two structurally different processes, quarrying in a rural setting and settlement expansion in a peri-urban one, produce comparable

NDDI values is itself worth noting: the index registers the absence of moist vegetation but does not distinguish what removed it.

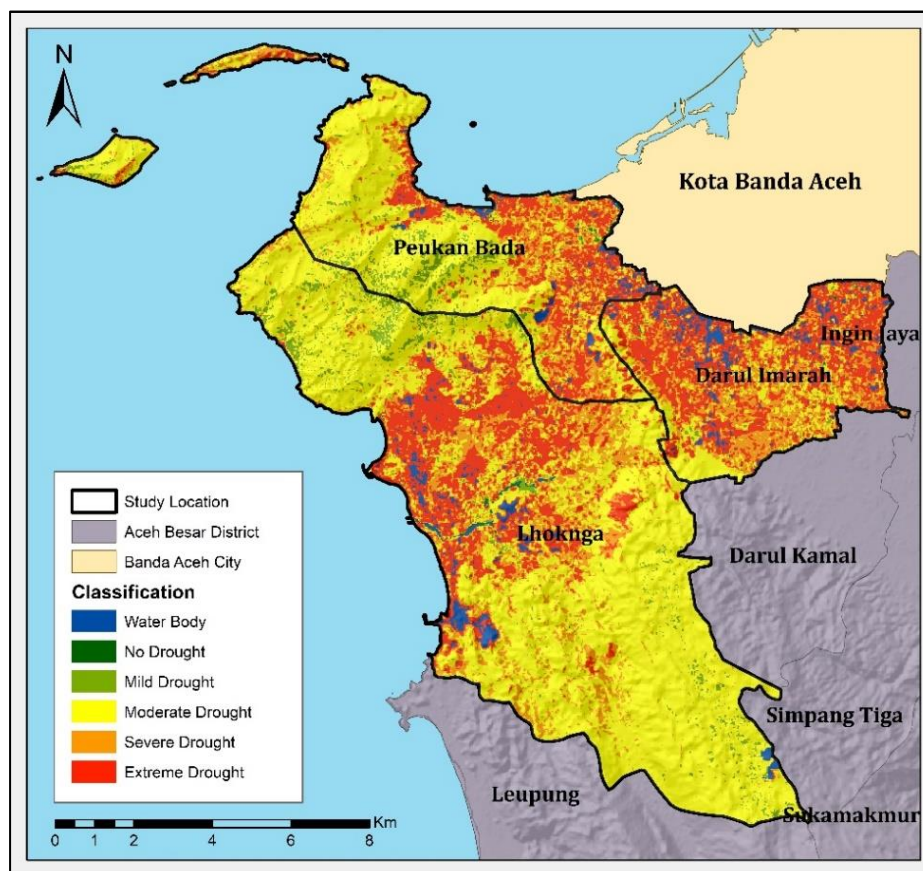


Figure 7. NDDI Classification at the Research Site

Table 4. NDDI Class Areas in the Study Area

Area (Ha)	Classification
425.06	Water Body
25.68	No Drought
546.47	Mild Drought
7,748.35	Moderate Drought
2,789.31	Severe Drought
3,076.08	Extreme Drought
14,610.95	Total classified

Source: Analysis, 2025.

The classified total falls 3.02 ha short of the administrative area of 14,613.97 ha, attributable to edge pixels excluded during masking. All study area shows extensive areas of extreme drought, indicated by the bright red colour on the map, where the NDDI value approaches 1. Areas with relatively lower values, corresponding to mild drought, are limited, and the blue distribution marks water bodies.

3.2. Meteorological Drought Conditions Based on SPI

SPI classification is presented in Figure 8, and the result stands in marked contrast to the preceding section. Conditions across the study area are overwhelmingly near normal, covering 14,604.67 ha, or 99.9% of the total, shown in green. Areas falling into the extremely dry class, shown in red, amount to only 9.30 ha, confined to a handful of small patches along the northern coastal margin adjacent to the Banda Aceh boundary. The mean SPI across the study area is 0.05, indicating that cumulative precipitation over the

observation period sat marginally above its long-term climatological average and that no meteorological drought signal is present at the annual scale. This says nothing about surface moisture, which SPI does not measure and which is addressed separately through NDDI.

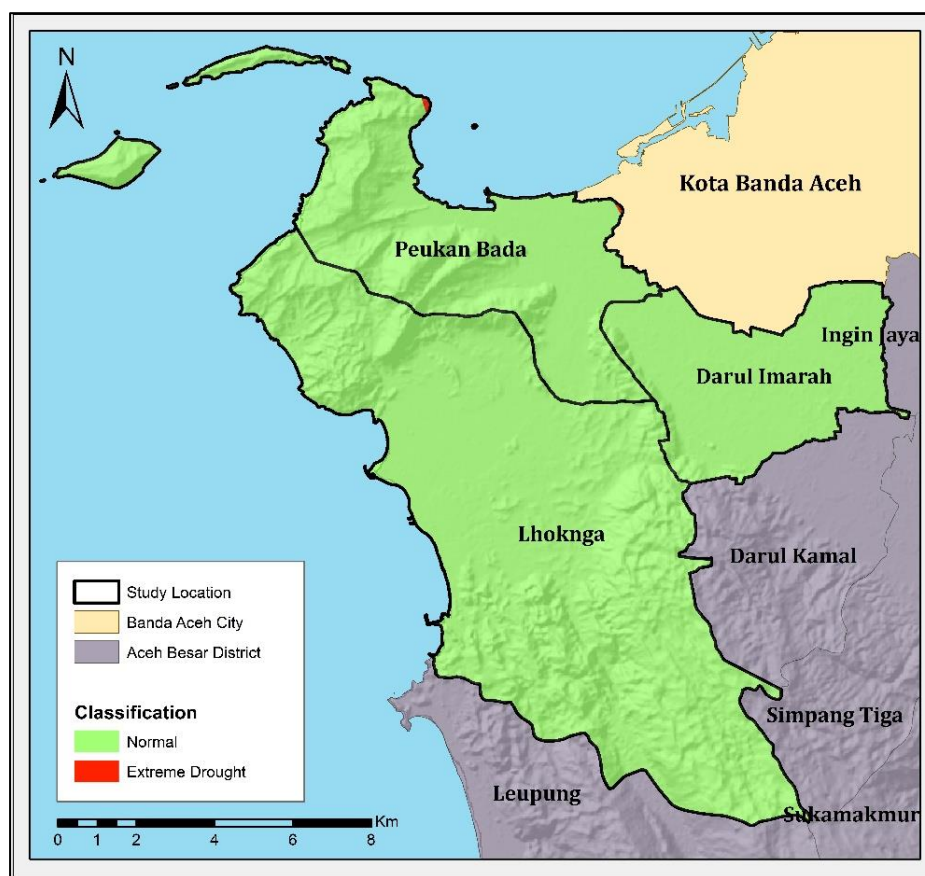


Figure 8. Classification of SPI at the Research Site

3.3. Divergence Between Meteorological and Vegetative Drought

Read side by side, Figures 7 and 8 describe two apparently incompatible conditions in the same territory during the same period. SPI places 99.9% of the study area in the near-normal range; NDDI places 93.2% in at least moderate drought. Rainfall, in other words, was not the problem. This divergence is the central finding of the study, and it carries a specific interpretation. Where precipitation is adequate but vegetation and surface moisture are depleted, the constraint lies not in the supply of water to the land surface but in the capacity of that surface to receive, retain, and make it available.

Three mechanisms plausibly contribute. Loss of vegetation cover reduces canopy interception and root-zone storage while raising surface temperature and evaporative loss. Degradation of soil structure, whether through compaction, sealing, or removal of topsoil, lowers infiltration and accelerates runoff. And the absence of managed retention means that what does fall drains rapidly out of the system rather than recharging it. The implication for drought monitoring is direct: a system relying on rainfall data alone would have reported no drought throughout the observation period, yet it is surface conditions that households and agricultural producers actually encounter. This does not make SPI redundant; it makes SPI insufficient on its own, and it establishes that in this setting the two indicators must be read together rather than treated as substitutes.

3.4. Water Carrying Capacity of Settlements

The map of water carrying capacity of settlements processed by geographic information systems shows high spatial variation between areas. The calculation of water carrying capacity is carried out using the variegated scale grid method, which divides the area into contiguous cells at the 5 by 5 arc-second resolution described in the methods. Water carrying capacity is calculated based on the ratio between water availability and water demand. Water availability (SA) is calculated from rainfall (CHIRPS), weighted runoff coefficient, and area. Meanwhile, water demand (DA) is based on the total population and Water Adequate Life Needs (KHLA) of 1,600 m³/capita/year, according to Permen LH No. 17 of 2009.

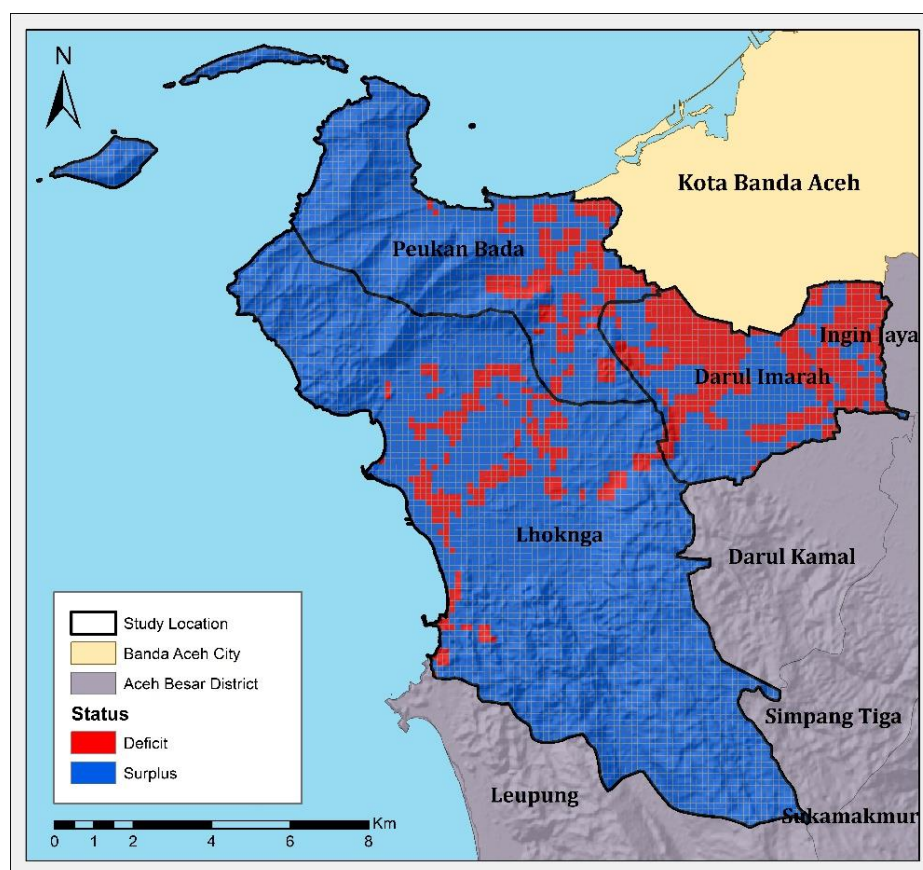


Figure 9. Water Carrying Capacity Status at the Research Site

Areas with high carrying capacity (dark blue color) only include areas that have high vegetation cover and low population density. In contrast, areas with a water carrying capacity deficit (red color), indicate a high population load and low water availability. The DDA is calculated based on a combination of annual water availability and per capita water demand, resulting in a map that divides areas into surplus, balanced and deficit status. The results show that approximately 2,454.68 hectares (17%) of the study area is in deficit of water carrying capacity, particularly in the dense settlement zones. In contrast, 12,159.28 hectares (83%) are in surplus, generally in highly vegetated areas far from settlement centres, as shown in Figure 9. Two observations follow. First, the deficit is a settlement phenomenon rather than a climatic one, since it tracks population density more closely than it tracks anything in Figures 7 or 8. Second, the 83% surplus figure should not be read as reassurance: a surplus computed as an annual balance can coexist with acute seasonal shortage, because it says nothing about whether water is available at the time and place it is needed. This limitation is particularly acute in karst terrain.

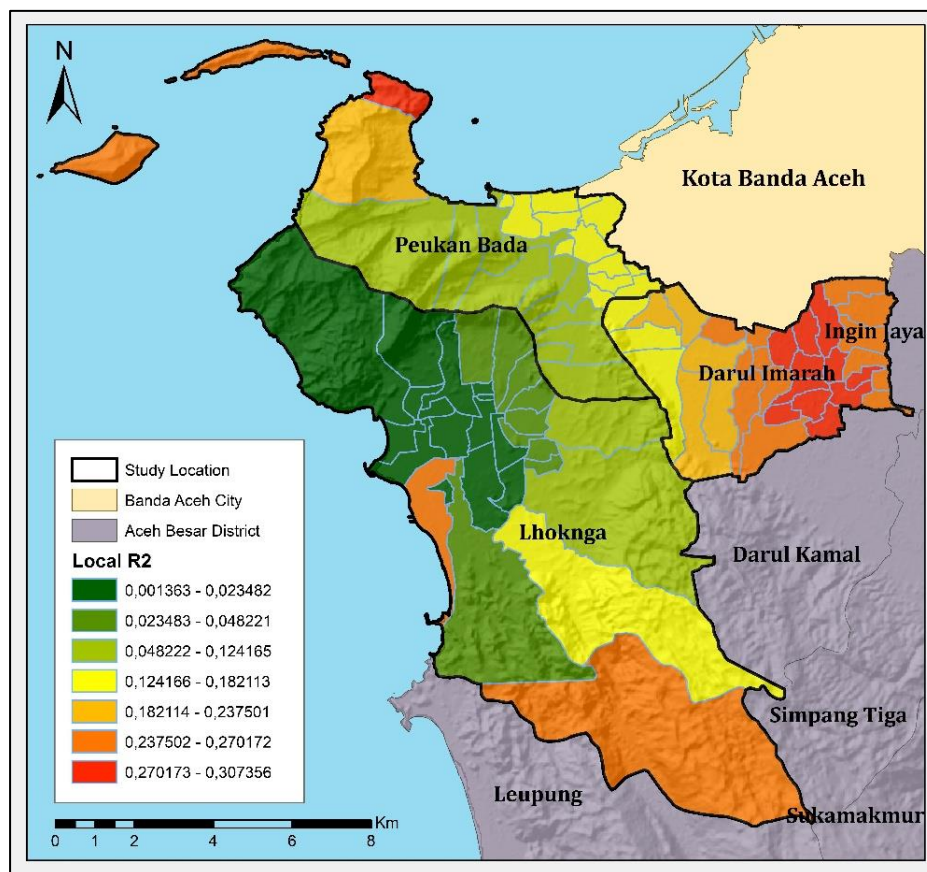


Figure 10. Local R^2 at the Research Site

3.5. Spatial Relationship Between Drought and Water Carrying Capacity

An analysis of the impact of drought distribution on the water carrying capacity of settlements was conducted using the Geographically Weighted Regression (GWR) approach. In the context of this study, the dependent variable used is the value of water carrying capacity, while the independent variable is the value of the drought index represented by the Normalized Difference Drought Index (NDDI) because, unlike SPI, it exhibits substantial spatial variation across the study area and therefore carries the variance a local regression requires. The model is designed to capture the non-stationarity of the relationship between variables at each location, so that the regression coefficient and determination value (R^2) can vary at each observation point.

Based on the results of spatial analysis using the GWR model, it shows that the distribution pattern of drought-prone areas has a varying influence on water carrying capacity. GWR processing results show that the value of the coefficient of local determination (Local R^2) ranges from 0.02 to 0.304. The highest value is found in the central and southern parts of Darul Imarah Subdistrict, with Local $R^2 > 0.27$. This suggests that in these areas, drought (NDDI) can explain up to 30% of the variation in water carrying capacity. In contrast, in most parts of Lhoknga and Peukan Bada sub-districts, Local R^2 values were below 0.15, indicating that the influence of NDDI on water carrying capacity in these areas is relatively weak. The distribution of Local R^2 values is visualized in the form of a thematic map, with green (very weak relationship) to red (strong relationship) color gradations. Figure 10 shows that the relationship between drought and water carrying capacity is spatially uneven, which confirms the premise that motivated the use of a local estimator: a global regression would have returned a single weak coefficient and concealed the fact that the relationship holds in one part of the study area while essentially failing in the others.

3.6. Factors Beyond Drought

If surface drought explains so little of the variation in water carrying capacity, what accounts for the remainder? Two mechanisms stand out, and both operate through pathways that a surface reflectance index cannot observe. One of them is the phenomenon of urban sprawl, which is the growth of cities or settlements that expand horizontally and uncontrollably to peripheral areas, characterized by low density, increased land consumption, and low green space planning. Lhoknga sub-district, although administratively a non-urban area, has experienced spatial pressure due to settlement expansion, especially in the western and southwestern parts close to the main access to Banda Aceh City.

The results of the calculation of the standardized residuals of the GWR model show values that fall within the range of -1.92 to +1.87, which is still within the standard range of ± 2 . These values indicate that the model does not show extreme deviations or strong spatial autocorrelation in the residual errors, so it can be concluded that the GWR model is generally valid for use in the context of this analysis. The residual surface, presented in Figure 11, shows no pronounced spatial clustering, which indicates that the model is not systematically misspecified over any part of the study area and that the low local R^2 values reflect genuinely weak association rather than model failure. It should nonetheless be stated plainly that a maximum local R^2 of 0.304 is a weak fit by any standard. Even at its best-performing location the model leaves roughly seven tenths of the variation unaccounted for, and across most of the study area considerably more. The productive reading is not that the analysis failed to find a relationship, but that it succeeded in showing where the expected relationship does not hold, and by how much.

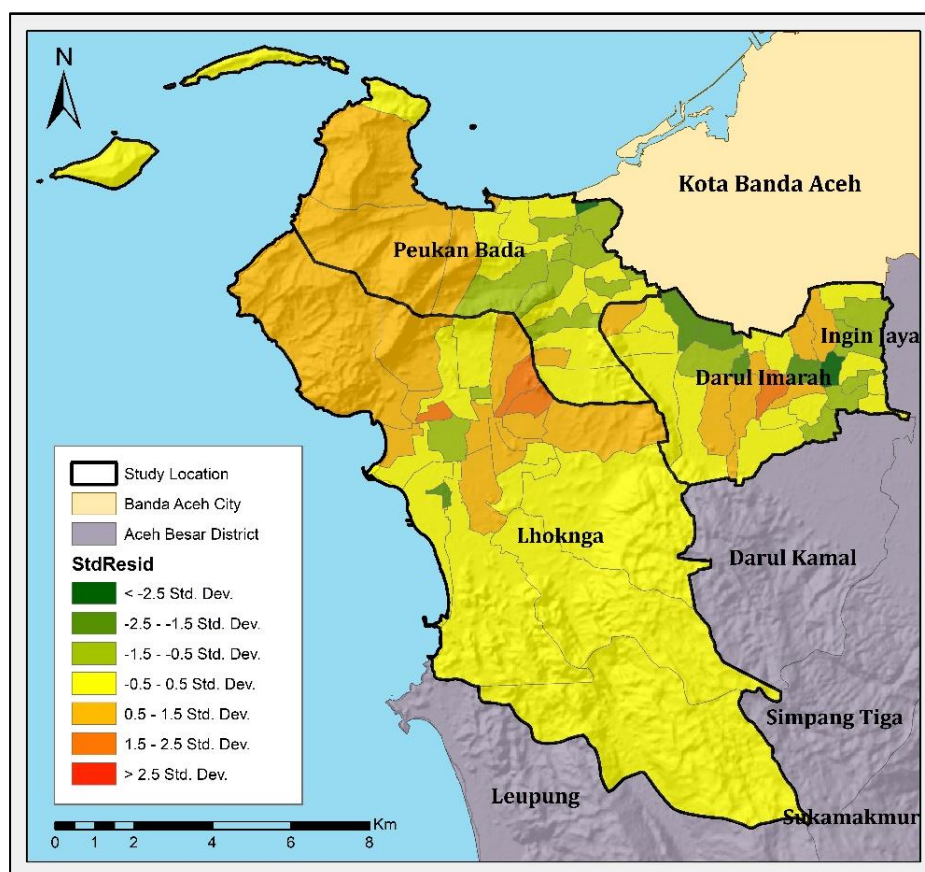


Figure 11. Standardized Residuals at the Research Site

The relationship between drought and water carrying capacity then becomes part of explaining the broader impacts. The water carrying capacity of settlements is calculated based on the ratio between water availability and population demand. Environmental carrying capacity theory explains that when the demand

for resources exceeds renewable supply, the system comes under stress; but that formulation treats the supply side as given, whereas the present results show it to be spatially contingent (Falkenmark et al., 1989), the environmental system is at risk of stress and malfunction (Budihardjo et al., 2013). One important factor is urban sprawl and the uncontrolled expansion of built-up areas. Urban sprawl has become the main characteristic of regional growth in Darul Imarah and Peukan Bada sub-districts, which are directly adjacent to the city of Banda Aceh. Based on Qanun Kabupaten Aceh Besar Nomor 4 Tahun 2013 Tentang Rencana Tata Ruang Wilayah Kabupaten Aceh Besar 2012–2032, Darul Imarah District is directed as a settlement service center, while Peukan Bada and Lhoknga are strategic tourism and coastal areas. The impact of urban sprawl often ignores ecological efficiency and creates new environmental burdens (Festus et al, 2020). Land conversion from vegetative areas as well as the impacts of climate change have contributed to a decrease in the soil's infiltration capacity of rainwater, which in turn increases the volume of surface runoff and accelerates the rate of soil drying (Ali et al., 2024).

These development dynamics lead to increased water demand, while the availability of clean water is often limited, especially in the dry season. This creates an imbalance between water supply and demand, potentially leading to a deficit in water carrying capacity. In addition, changes in rainfall patterns and climate anomalies such as El Niño play a major role in expanding the scope and intensity of drought in the tropics (Aditya et al., 2021). Darul Imarah sub-district and its surroundings are characterized by karst landscapes that are known for their high infiltration but low surface water storage capacity. Karst aquifer systems are often unable to store water effectively for long periods of time, making the region vulnerable to drought despite high annual rainfall. The limited water retention in karst areas means that settlement water supply is highly dependent on artificial water distribution or deep groundwater. The conversion of vegetative land into built-up areas also leads to increased runoff coefficients, reduced water infiltration, and accelerated decline in groundwater reserves, significantly compromising water carrying capacity.

In a biophysical context, karst areas in Darul Imarah sub-district also play an important role in explaining the weak relationship between NDDI and water carrying capacity. Karst areas naturally have low groundwater storage capacity due to their porous geologic structure and rock cracks. However, the degradation of karst areas due to limestone mining, land clearing for tourism and deforestation activities has exacerbated this condition. The Mata le karst massif on the southern edge of Darul Imarah offers a documented illustration: quarrying, land clearing for tourism, and progressive deforestation there have reduced vegetation cover to <75% and caused land morphology changes of 30-50%. This karst degradation has resulted in the loss of the aquifer's natural function as a long-term water store (Avrilan et al., 2022). The resulting hydrological system responds quickly to rainfall and drains just as quickly, leaving little to draw on when the dry season arrives. This matters directly for the interpretation of the GWR results: subsurface storage loss of this kind is invisible to NDDI, which senses only the uppermost layers of vegetation and soil moisture, yet it is decisive for water carrying capacity. Index and outcome are therefore decoupled by construction precisely where karst dominates, which offers one concrete explanation for the low local R^2 values observed across much of the study area.

4. CONCLUSIONS

This study set out to map drought distribution and water carrying capacity across three sub-districts of Aceh Besar Regency and to determine how the two relate across space. Three findings emerge. First, meteorological and vegetative drought diverge sharply in this setting. SPI over the period 1994 to 2024 places 14,604.67 hectares, essentially the entire study area, in the near-normal precipitation range, with only 9.30 hectares classified as extremely dry, while NDDI places 13,613.74 hectares, or 93% of the area, in at least moderate drought. Rainfall was adequate; the land surface was not. Rainfall-based monitoring taken alone would therefore have reported no drought in a territory where surface conditions were severely stressed, which makes vegetative indicators a necessary complement rather than a supplement. Second, water carrying capacity is under pressure in the settled parts of the study area: 2,454.68 hectares, or 17%, fall into deficit, concentrated in Darul Imarah, the sub-district with the largest population on the smallest land area,

while the remaining 12,159.28 hectares register surplus. Third, the spatial pattern of the relationship is itself a finding. High local R^2 values in central and southern Darul Imarah indicate that where settlement density is greatest, carrying capacity does track the vegetative drought signal closely, so NDDI has diagnostic value there. Low values across Lhoknga and Peukan Bada indicate the opposite: these areas register ecologically extreme drought under NDDI, yet their water balance is governed by factors the index does not observe, principally karst hydrogeology and low population load. Satellite-based drought monitoring combining NDDI with GWR modelling is therefore useful for locating environmental stress on water resources, but it is not sufficient on its own to explain the full set of factors that shape carrying capacity.

Several limitations qualify these results. The GWR model was specified with a single predictor, and a maximum local R^2 of 0.304 means that even in the best-fitting locations roughly seven tenths of the variation remains unaccounted for. The analysis rests on a single annual composite for the reference year, which cannot distinguish a structural condition from an anomalous one. SPI, by design, omits evaporative demand, so the near-normal precipitation it reports may understate actual atmospheric water stress under tropical conditions. Water availability was estimated from rainfall and runoff coefficients alone, without direct observation of groundwater levels or of the karst aquifer that this paper argues is decisive. Finally, results are reported for the combined study area rather than disaggregated by sub-district; while the maps permit qualitative comparison between the three, a quantitative cross-tabulation of drought class against administrative unit would allow the inter-sub-district contrasts described here to be tested rather than observed.

These limitations define a clear agenda. Extending the analysis to a multi-year time series would separate structural drought from interannual variability and permit trend detection. Introducing additional predictors into a multiscale GWR specification, in particular built-up density, land cover change, and a proxy for karst extent, would test directly whether the unexplained variance is attributable to the mechanisms proposed here rather than inferred from their absence. Comparing SPI against SPEI over the same period would establish how much of the observed divergence is an artefact of omitting evapotranspiration. Most usefully, field validation through groundwater level measurement and household water use surveys in the deficit zones of Darul Imarah would allow the grid-based estimates to be calibrated against observed conditions rather than assumed per capita standards.

It is necessary to develop a regular spatial data-based drought monitoring system by utilizing platforms such as Google Earth Engine to support early warning systems. The Aceh Besar District Government is also advised to prioritize the development of clean water infrastructure in areas experiencing deficits, especially dense residential areas. Groundwater management in coastal and karst areas requires an approach adapted to local hydrogeology: uniform abstraction standards are inappropriate where aquifer storage varies as sharply as it does across this study area, and karst zones in particular warrant abstraction limits set against measured storage rather than against rainfall. In addition, the results of this study need to be integrated in spatial planning such as RTRW and RDTR, with a location-based approach through Geographically Weighted Regression (GWR) analysis to support sustainable development.

5. ACKNOWLEDGMENTS

The authors gratefully acknowledge the Department of Architecture and Planning, Faculty of Engineering, Universitas Syiah Kuala, for the institutional support that made this research possible. We thank Statistics Indonesia (BPS) for population data on Aceh Besar Regency, the Geospatial Information Agency (BIG) for administrative and road network datasets, and the Aceh Disaster Management Agency (BPBA) for access to regional disaster records. We also acknowledge the Google Earth Engine platform and the CHIRPS and Landsat programmes for making satellite and precipitation archives openly available, and colleagues who assisted with spatial data provision and interpretation of the analysis. We thank the anonymous reviewer whose comments substantially improved the structure and argument of this manuscript.

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