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Geospatial Monitoring and Hazard Assessment of Agricultural Drought Using GIS and Remote Sensing in Bay Region of Somalia

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Abstract
Agricultural drought represents a major environmental challenge impacting the Horn of Africa, especially Somalia's Bay region. Bay, a semi-arid region dependent on rain-fed agriculture and pastoralism, is significantly susceptible to the effects of recurring droughts, which threaten food security, reduce agricultural production, and increase humanitarian disasters. The main objectives of this study were to: Analyze spatiotemporal variability in drought conditions using satellite-based indices. The research utilized essential remote sensing indices, specifically the Vegetation Health Index (VHI), which is derived from the Normalized Difference Vegetation Index (NDVI) and the Temperature Condition Index (TCI). Data from Landsat satellites were analyzed with GIS technologies to categorize drought severity into five classifications: Extreme, Severe, Moderate, Mild, and No Drought. The investigation encompassed the years 2014, 2016, 2018, and 2020 to assess temporal changes and spatial distribution. The analysis was carried out using ArcGIS 10.8. The VHI results showed significant fluctuations over the study period. In 2014, severe to extreme drought covered over 54% of the region, with less than 1% unaffected. By 2016, conditions improved slightly, with mild drought covering 34% and drought-free areas rising to 12%. In 2018, drought severity escalated, with extreme drought expanding to 31%, while areas without drought declined to 7.4%. By 2020, drought conditions peaked, with over 90% of the region experiencing moderate to severe stress and only 0.3% free from drought. The findings underscore the region's vulnerability to climatic variability and the need for robust early warning systems. The study demonstrates the efficacy of GIS and remote sensing in drought monitoring, providing actionable insights for policymakers and humanitarian agencies to enhance resilience in Gedo and similar arid regions.

Keywords: Agricultural Drought, Bay Region, GIS, Remote Sensing, VHI.

Introduction

Somalia is recognized as one of the most drought-prone nations globally, facing frequent and severe dry periods that continually threaten livelihoods and food security. The nation's arid and semi-arid climate, fragile ecosystems, and heavy reliance on rain-fed agriculture and pastoralism make it highly susceptible to rainfall fluctuation and extended dry spells [1]. Drought cycles have escalated in recent decades, with major occurrences noted in 2010–2011, 2016–2017, and from 2020 onwards, consistently leading to mass displacement, animal mortality, and famine [2]. The humanitarian impact is profound, with millions of Somalis experiencing food insecurity due to the complex interaction of drought, conflict, poverty, and governance issues [3].This situation highlights a critical need for robust and timely drought monitoring to safeguard the country's vulnerable agricultural sectors.

Effective agricultural drought monitoring is essential in Somalia, particularly in regions like the Bay region, often referred to as the nation's "breadbasket." However, the Bay region, and by extension other crucial areas, exhibit inadequate adaptive capacity, frequent rainfall deficits, and insufficient early warning systems [3].Conventional meteorological data collection in such regions is often limited, posing a challenge for prompt and precise intervention [4]. While previous studies have utilized Geographic Information Systems (GIS) and remote sensing for drought delineation using indices like the Standardized Precipitation Evapotranspiration Index (SPEI) and the Reconnaissance Drought Index (RDI) across Somalia [1,2], comprehensive, high-resolution analyses using a combination of vegetation-specific indices are still needed for areas experiencing acute vulnerability. Research on regional variations in drought hazard levels indicates that while some areas are designated as extremely susceptible, a deeper spatio-temporal analysis is required to inform micro-level planning.

This study addresses the aforementioned gaps by focusing on the Gedo region of Somalia, utilizing the advanced capabilities of GIS and remote sensing technology to specifically monitor and evaluate agricultural drought. The novelty lies in the integrated application and analysis of multiple satellite-derived indicators—specifically the Normalized Difference Vegetation Index (NDVI), Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and the Vegetation Health Index (VHI). By consolidating multi-source data (climate and vegetation health) into a unified, spatially explicit platform, this research offers a more precise and comprehensive assessment of vegetation stress and agricultural dryness than previously available.

The main aim of this study is to explore spatiotemporal changes in drought conditions within the Gedo region and to identify and map drought-prone areas through the analysis of these satellite-derived indicators, utilizing robust GIS-based methodologies. The findings will provide essential data for formulating timely, location-specific interventions, thereby contributing to the development of enduring resilience against climatic shocks.

Materials And Methods

Study Area

The Bay region, an administrative area in southern Somalia situated at latitude 3° 04' 16.80" N and longitude 43° 50' 4.19" E, faces significant challenges due to inter-clan conflicts. According to Barrow (2020), these conflicts are primarily fueled by disputes over land, resources, and political power, particularly within the Baidoa district. The ongoing strife has severely compromised the region's security infrastructure. Furthermore, the area's capacity for livestock production, which holds considerable potential, is significantly undermined by both natural and human-induced constraints (Birhan, 2013).

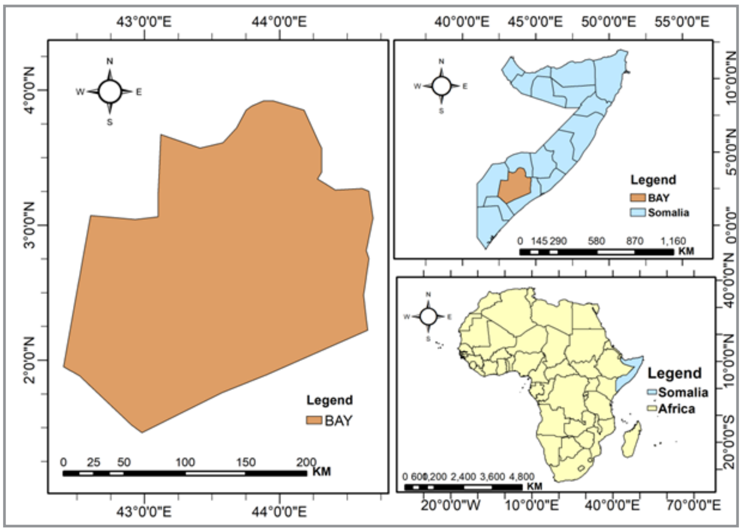

Figure 1: Study Area Map

Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) involves a simple mathematical formula:

(NIR-VIS) / (NIR+VIS),

where NIR is the near-infrared band and VIS is the visible red band (Lemenkova, 2015). This index is widely used in remote sensing to monitor vegetation health and changes over time. It has been successfully applied in various fields, including agriculture (Berger, 2019) and remote sensing (Zhang, 2020). The NDVI is particularly useful in predicting crop growth and yield, with a high correlation between the index and these outcomes (Berger, 2019). Furthermore, the index can be improved through fusion techniques, which enhance the spatial resolution of the NDVI (Zhang, 2020).

Normalized Difference Water Index (NDWI)

NDWI was measured following established methods [5, 6] Roberts et al., 2006; Ding & Gong, 2011). It is widely used to monitor changes in water content in vegetation, map water bodies, and assess aquatic vegetation. In this study, NDWI was applied to evaluate variations in vegetation water content across the study area.

Normalized Difference Built-up Index (NDBI)

NDBI was calculated following standard procedures [7, 8]. It is commonly used for mapping urban areas and delineating built-up regions from natural landscapes. This index exploits the fact that built-up areas reflect more in the shortwave infrared spectrum than vegetation, allowing accurate assessment of urban expansion.

Vegetation Condition Index (VCI)

VCI was derived based on the method by [9]. It measures vegetation condition by comparing current NDVI values with historical ranges over a similar time period. VCI is widely applied to monitor vegetation health and detect areas under drought stress.

Temperature Condition Index (TCI)

TCI was calculated following Kogan (2000). It assesses thermal conditions using land surface temperature (LST) data, providing insights into plant stress induced by temperature extremes. TCI complements VCI by integrating thermal information in vegetation monitoring.

Vegetation Health Index (VHI)

VHI was computed as an integration of VCI and TCI following [10]. By combining vegetation greenness and thermal conditions, VHI offers a comprehensive assessment of vegetation health and drought impact across the study area.

GIS Tool

In this study, Geographic Information Systems (GIS) were employed as a fundamental analytical framework to assess and map the spatial patterns of agricultural drought in the Bay region of Somalia. GIS enabled the integration of multi-source spatial data, including satellite imagery, vegetation indices (NDVI, VCI, TCI, and VHI), land surface temperature (LST), and precipitation anomalies. The analysis was conducted using ArcGIS software, which facilitated data pre-processing, classification, overlay analysis, and map generation. GIS tools were particularly instrumental in visualizing temporal changes in vegetation health and identifying drought-prone areas across different years (2014, 2016, 2018, and 2020). The thematic maps created through GIS allowed for a clearer understanding of drought severity at the regional and sub-regional levels. Spatial statistics such as zonal analysis and pixel classification further enhanced the accuracy of drought impact assessments. Moreover, GIS supported the development of drought hazard maps by combining environmental indicators with administrative boundaries, enabling policymakers and humanitarian agencies to prioritize high-risk areas. The integration of GIS with remote sensing tools provided a cost-effective, scalable, and reliable methodology for drought monitoring in data-scarce regions like Somalia (Tadesse et al., 2015; AghaKouchak et al., 2015),[11].

Data Sources

All spatail and remote sensing data utalized in this study sourced from united state gealogical survey (USGS). This platform provided access to high-resolution satellite imagery, including Landsat 8 data, which was used to derive key drought indicators such as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI). The data from USGS Earth Explorer are freely available and widely used in environmental monitoring and drought assessment due to their reliability, temporal consistency, and spatial coverage.

All datasets were downloaded in GeoTIFF format and processed using GIS and remote sensing software tools. The time-series analysis covered the years 2014, 2016, 2018, and 2020 to examine spatiotemporal drought patterns.

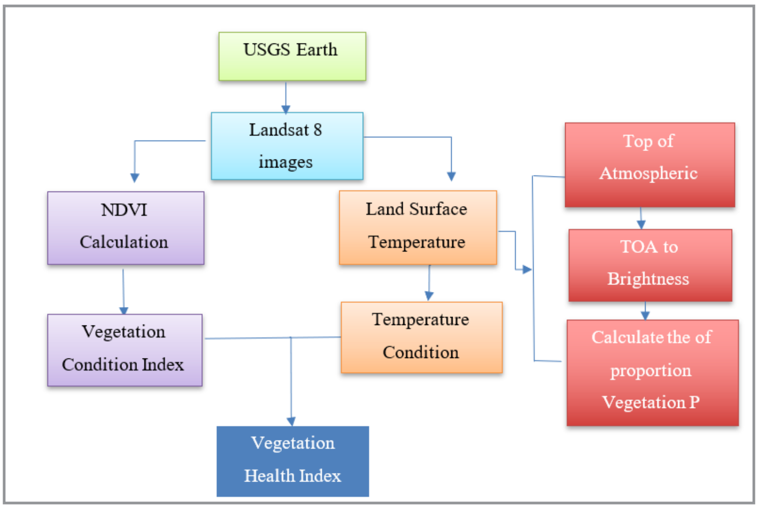

Figure 2: Flow Chart Methodology

Results and Discussion

Normalized Difference Vegetation Index (NDVI)

2014, NDVI analysis showed low to moderate vegetation cover, with values ranging from 0.0037 to 0.60. Values below 0.1 indicated barren land, such as sand and rocks, particularly in the western and southern regions, while values above 0.1 suggested better vegetation in the northeast (Guliyeva, 2020). By 2016, NDVI values ranged from 0.006 to 0.57, reflecting modest improvements in some areas due to more favorable rainfall, although vegetation density remained lower than peak conditions of 2014. In 2018, NDVI values broadened from −0.034 to 0.56, with negative values indicating degraded or barren areas, while higher values in localized patches suggested persistent vegetation health in northern and eastern regions, likely influenced by irregular rainfall and land degradation. The 2020 analysis exhibited values from 0.0066 to 0.56, showing partial recovery in central and northern regions, although large areas continued to face stress and drought vulnerability (FSNAU, 2023).

These observed trends can be attributed to several factors. Variability in rainfall and drought severity strongly affects vegetation growth, with low NDVI values coinciding with drought periods [12]. Land degradation due to overgrazing or unsustainable land use may also contribute to negative NDVI values (PLOS ONE, 2024). Comparisons with recent studies indicate that NDVI remains a useful indicator of vegetation stress, but its correlation with ground-based observations in Somalia has declined in some regions, suggesting that integrating NDVI with other indices such as SPEI, soil moisture, and VHI may provide more reliable drought monitoring [13], PLOS ONE, 2024).

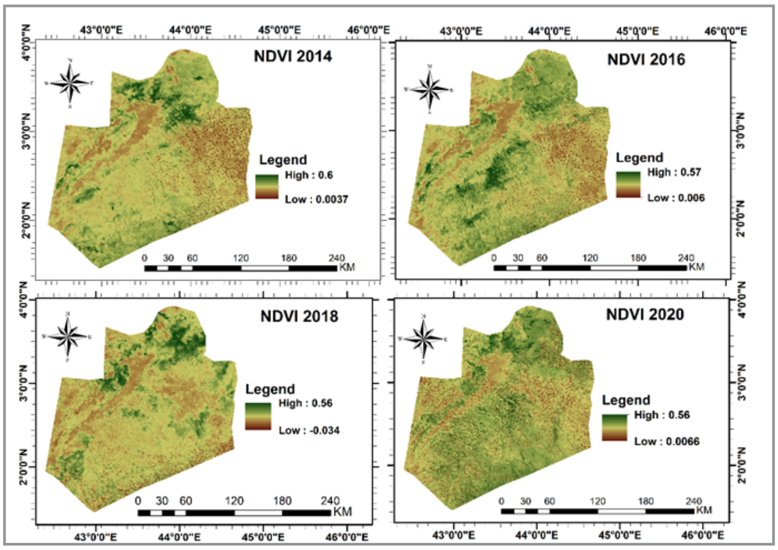

Figure 3: NDVI From 2014,2016,2018,2020

Normalized Difference Water Index (NDWI)

In 2014, NDWI values ranged from -0.25 to 0.16, reflecting generally low water availability across the region. Most areas showed negative values, indicating dry conditions, while only a few pockets mainly in the east retained some surface moisture. By 2016, the range shifted slightly to -0.25 to 0.18, suggesting a modest improvement, particularly in the northeast and central parts, likely linked to better rainfall. In 2018, values spread more widely, from -0.28 to 0.22, pointing to greater variation in water availability: some areas benefited from improved moisture, while others became drier, hinting at uneven rainfall and changing land surface conditions. By 2020, NDWI values reached -0.25 to 0.23, showing minor improvement. The observed decline in wetness is consistent with [14],who reported that moderate and high wetness areas in the Ciletuh Geopark decreased by almost 50% between 2001 and 2015, demonstrating NDWI's effectiveness in monitoring wetness status and drought impacts. Lower or negative NDWI values suggest dry conditions and sparse cover, while higher NDWI values imply increased vegetation water content and fractional canopy cover [5].

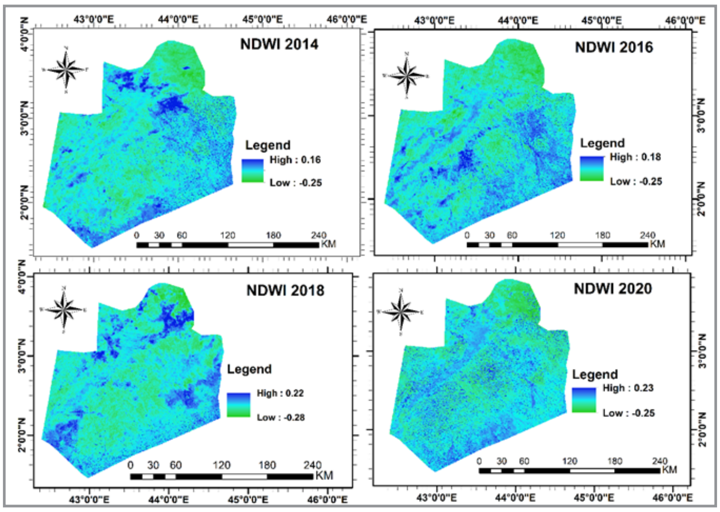

Figure 4: NDWI From 2014,2016,2018,2020

NDBI (Normalized Difference Built-up Index)

In 2014, NDBI values ranged from -0.16 to 0.25, with negative values indicating vegetated or natural surfaces and positive values marking areas of stronger built-up intensity. This suggests that much of the region was dominated by natural cover, while built-up activities were concentrated mainly in the northern and central zones. By 2016, values shifted slightly to between -0.18 and 0.25, showing modest expansion of built-up surfaces, particularly in central and eastern parts of the region, reflecting growing land use pressure and settlement growth. In 2018, the range widened further, from -0.22 to 0.28, marking the highest maximum recorded during the study period. This increase highlights intensified urban presence, while the lower minimum values emphasize areas that remained less developed and more vegetated. By 2020, NDBI values ranged from -0.23 to 0.25, showing that built-up zones persisted across the northeast and southern parts of the region, indicating that urban expansion and land modification remained a defining feature of the landscape. These observations align with previous studies that have applied NDBI to monitor urban growth and built-up expansion, confirming its effectiveness in reflecting changes in land use and settlement patterns [7, 14, 15].

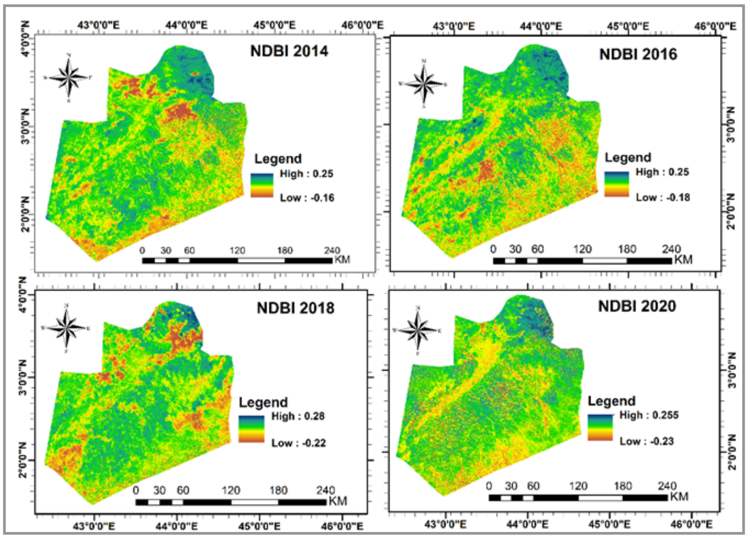

Figure 5: NDBI From 2014,2016,2018,2020

Temperature Condition Index (TCI)

TCI analysis revealed notable shifts in temperature-related conditions, with values ranging from -0.39 to 0.836 across the study period. In 2014, values spanned -0.39 to 0.78, reflecting considerable variation, with low values indicating potential heat stress and higher values pointing to more favorable conditions for vegetation. By 2016, the range narrowed to -0.3 to 0.58, suggesting reduced variability but also an increase in temperature-related stress, which likely limited vegetation resilience. In 2018, the TCI broadened again, from -0.3 to 0.72, marking some recovery in favorable conditions, though persistent low values highlighted ongoing stress in parts of the region. By 2020, the index reached its highest maximum of 0.836 and a minimum of -0.15, suggesting overall improvement, with fewer extreme low values and more favorable thermal conditions for vegetation growth. These dynamics align with previous studies that confirm TCI as a reliable indicator for monitoring drought-related thermal stress in arid and semi-arid environments [9-8]. The findings emphasize that vegetation in the region is highly sensitive to temperature fluctuations, and improving early detection of drought stress through indices like TCI is crucial for developing effective adaptation and management strategies.

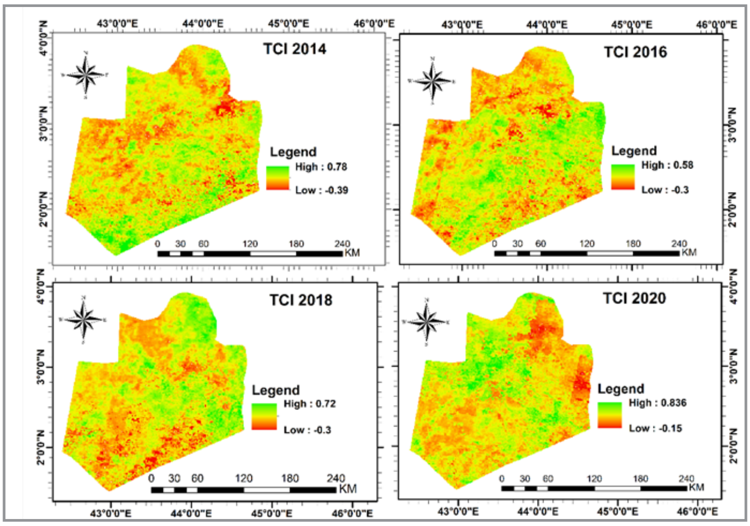

Figure 6: TCI From 2014,2016,2018,2020

Vegetation Condition Index (VCI)

Between 2014 and 2020, the VCI analysis unveiled dynamic variations in vegetation condition, with values ranging from -0.45 to 7.75 across the study period. In 2014, VCI values spanned -0.13 to 4.9, suggesting moderate variation, with higher values indicating relatively healthier vegetation and lower values highlighting areas of stress or poor cover. By 2016, the range narrowed to -0.3 to 3.5, and the reduction in maximum values pointed to an overall decline in vegetation condition, with stress likely affecting larger portions of the region. In 2018, the values expanded again to between -0.345 and 5.5, showing partial recovery as vegetation improved in some areas, though the persistence of low values indicated continued stress across others. By 2020, the range widened further to -0.45 to 7.75, marking the highest maximum value in the study period and suggesting a notable improvement in vegetation condition in several zones, even as the more negative minimum values confirmed ongoing stress in parts of the landscape.

These findings align with earlier research that highlights VCI as a reliable index for detecting vegetation stress and distinguishing between seasonal and long-term drought effects [10-16]. further emphasized its usefulness in capturing vegetation responses to climatic fluctuations in semi-arid environments.

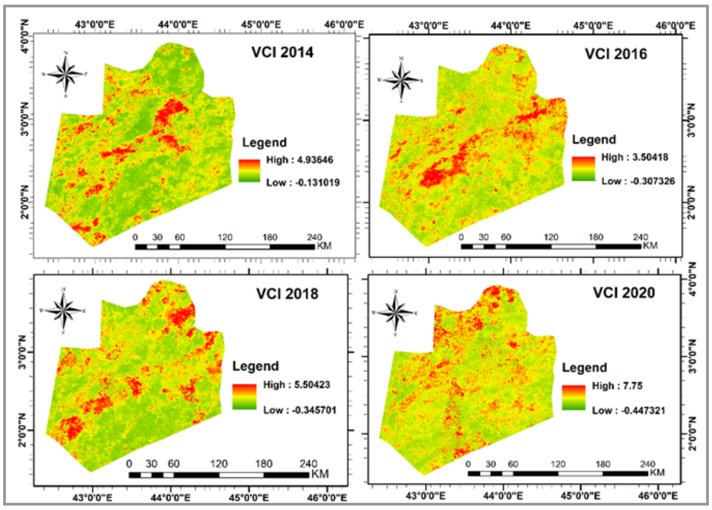

Figure 7: VCI 2014,2016,2018,2020

Vegetation Health Index (VHI)

The Vegetation Health Index (VHI) provides a comprehensive measure, incorporating both vegetation condition and thermal stress factors. The analysis delineates drought classes over several years, specifying the area in hectares and the corresponding percentage of total area affected. These classes range from 'No Drought' to 'Extreme Drought,' with VHI values serving as the basis for classification.

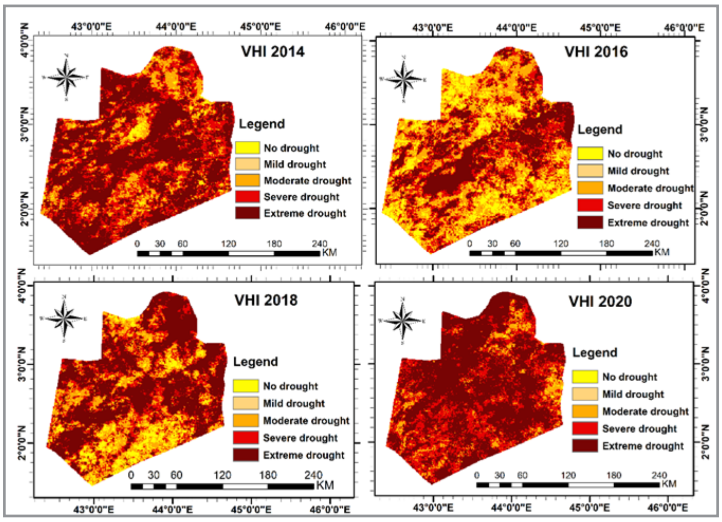

Figure 8: VHI 2014, 2016, 2018, 2020.

Distribution Vegetative Health Index 2014

The VHI analysis for 2014 shows that drought was widespread across the study area. Only 1.53% of the land experienced no drought conditions, expressing very limited presence of healthy vegetation. About 14.62% of the area was under mild drought, while nearly 29.54% faced moderate drought, highlighting vegetation stress due to limited rainfall and soil moisture. The drought impact was more severe in the remaining areas, with 24.84% of the land affected by severe drought and the largest share, 29.46%, experiencing extreme drought.

The VHI analysis for 2014 clearly indicates that a vast majority of the Bay region was subjected to moderate to extreme drought conditions, signifying that 2014 was a year of critical vegetation stress and water scarcity. Previous research supports this observation, as VHI is widely recognized for its effectiveness in integrating both vegetation and temperature data to assess drought severity more comprehensively [17]. Studies such as [18] also demonstrate that VHI is particularly useful for detecting agricultural drought and mapping its spatial extent in regions prone to water scarcity.

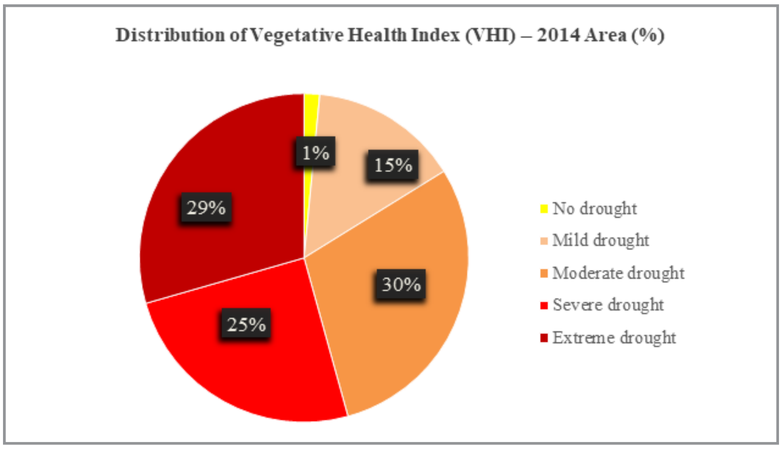

Figure 9: Distribution of Vegetative Health Index 2014

Distribution Vegetative Health Index 2016

In 2016, the Vegetation Health Index (VHI) revealed varying drought conditions across the study area. Analysis of the data shows that 12.27% of the total area experienced no drought, indicating regions with normal vegetation health. Areas under mild drought constituted the largest portion, covering 34.15% of the land, suggesting extensive but low-intensity stress on vegetation. Moderate drought affected 27.63% of the area, reflecting significant vegetation stress requiring attention. Severe drought conditions were observed in 13.90% of the region, representing areas with high vegetation stress. Lastly, extreme drought impacted 12.03% of the total area, highlighting critical zones where vegetation health was severely compromised. These percentages demonstrate that in 2016, a majority of the study area experienced some level of drought, with mild and moderate droughts accounting for over 60% of the land, emphasizing the need for targeted drought mitigation strategies. Prior research highlights VHI as a valuable tool for assessing vegetation responses to drought, as it combines thermal and vegetation stress indicators [19]. [20] further noted that increases in extreme drought, as identified by VHI, are often linked to extended periods of rainfall shortage and elevated land surface temperatures in high-risk areas.

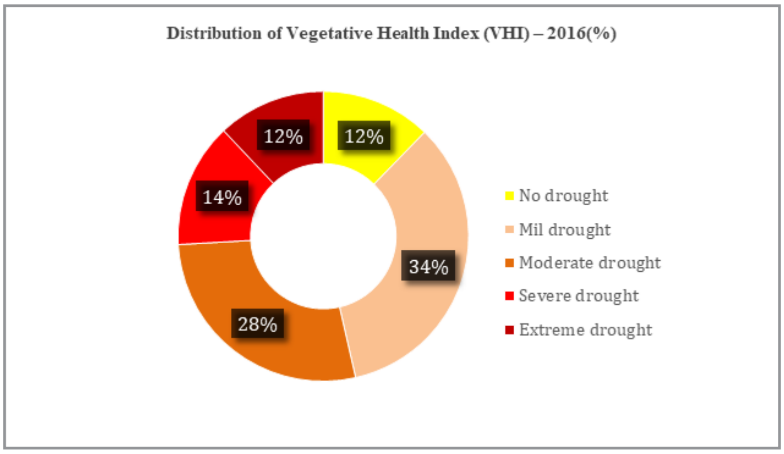

Figure 10: Distribution of Vegetative Health Index 2016

Distribution Vegetative Health Index 2018

The VHI analysis for 2018 shows that drought was extensive across the Bay region. Only 7.39% of the land experienced no drought conditions, indicating that healthy vegetation was scarce, while the largest share, 31.26%, experiencing extreme drought.

About 21.63% of the area was under mild drought, and 23.17% faced moderate drought, reflecting substantial vegetation stress due to inadequate rainfall and limited soil moisture. The drought situation was more severe in other areas, with 16.56% of the land affected by severe drought and The 2018 VHI distribution highlights a critical year of drought stress, with 54% of the region under some level of drought particularly dominated by extreme and moderate categories. Similar patterns have been observed in other drought-prone regions, where prolonged dry periods and rising temperatures have exacerbated vegetation stress, as identified using VHI [18]. Additionally, studies by [21] confirm that high proportions of land under extreme drought, as reflected in VHI, are often correlated with reduced crop yields and increased vulnerability in rural communities.

The relatively low percentage of areas with no drought further underscores the fragility of vegetation cover and agricultural systems in the Bay region. These findings reinforce the role of VHI as a valuable decision-support tool for agricultural planning, drought forecasting, and the development of climate adaptation policies.

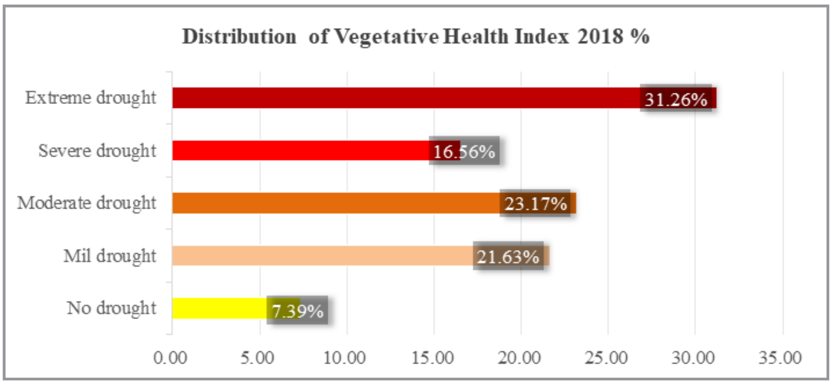

Figure 11: Distribution of Vegetative Health Index 2018

Distribution Vegetative Health Index 2020

The VHI assessment for 2020 reveals that drought conditions were dominant across the study area. Only 0.30% of the land remained free from drought, indicating an almost negligible extent of healthy vegetation. Approximately 8.22% of the region experienced mild drought, while about 28.68% was classified under moderate drought, reflecting considerable stress on vegetation due to insufficient rainfall and declining soil moisture. More critical impacts were observed in the rest of the area, with 27.28% falling into severe drought and the largest proportion, 35.52%, affected by extreme drought.

Overall, the VHI results for 2020 demonstrate that the majority of the Bay region was under moderate to extreme drought, signifying that the year was marked by pronounced vegetation stress and significant water scarcity.

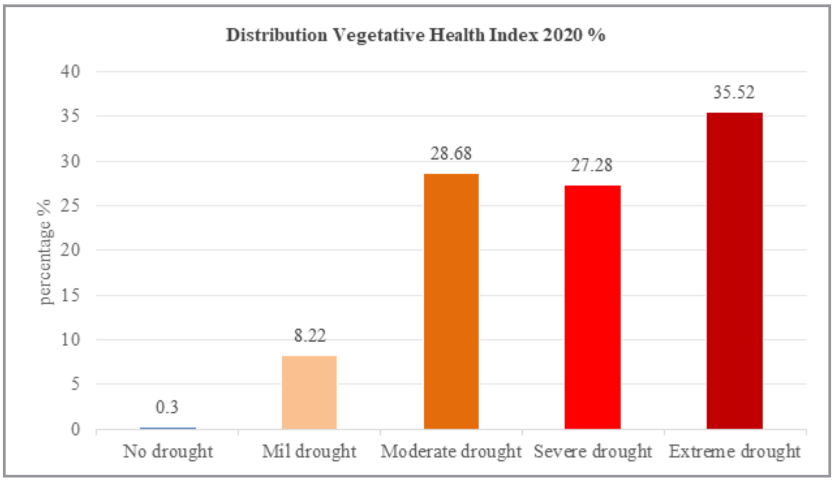

Figure 11: Distribution Vegetative Health Index 2020

Conclusion

The analysis of agricultural drought in Somalia's Bay region utilizing the Vegetation Health Index (VHI), which integrates the Normalized Difference Vegetation Index (NDVI) and the Temperature Condition Index (TCI), confirms the area's extreme vulnerability to climatic variability. The study demonstrates the efficacy of Geographic Information Systems (GIS) and remote sensing as a reliable methodology for monitoring and mapping drought severity in data-scarce, semi-arid environments.

The spatiotemporal VHI analysis across the study period (2014, 2016, 2018, and 2020) reveals a concerning pattern of increasing drought intensity [22]. In 2014, a vast majority of the region experienced moderate to extreme drought conditions, with only 1.53% of the land free from drought [23]. Conditions improved slightly in 2016, with mild and moderate drought covering over 60% of the land and drought-free areas rising to 12.27%. However, severity escalated in 2018, [24] with the largest share of the region (31.26%) experiencing extreme drought, while areas with no drought declined to 7.39%. The drought peaked in 2020, when over 90% of the region was classified under moderate to extreme drought, and a near-negligible 0.30% of the land remained free from drought, signifying pronounced vegetation stress and severe water scarcity [25].

The consistent findings from the Vegetation Condition Index (VCI) further indicate a persistent, moderate level of drought stress on plants, underscoring the region's limited adaptive capacity.

Declarations

Author Contribution Statement

Assuming the corresponding author, Abdiaziz Hassan Nur, is A.H.N. (the author marked with an asterisk), and the other authors are M.D.A. (Mohamed Dayib Abubaka), A.A.M. (Abdinasir Abdullahi Mohamed), and Y.A.H. (Yacqub Abdikadir Hussein), here is the revised Author Contribution Statement based on the provided placeholder structure and the new format

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Ethics Approval

This study did not involve any animal or human participant and thus ethical approval was not applicable

Consent for Publication

All co-authors gave their consent to publish this paper in AAES.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Supplementary Data

No supplementary data is available for the paper.

Funding Statement

Not applicable.

Additional Information

No additional information is available for this paper.

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