Case Study

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Comparative Analysis Of Remote-Sensing-Based Drought Indices (Tci, Vci, And Vhi) For Monitoring Drought Conditions During The 2015 El Niño Event.

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ABSTRACT

This study presents a comprehensive comparison of three widely utilized remote-sensing-based drought indices: the Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI). It focuses on their effectiveness in monitoring drought conditions in Tehran during the significant 2015 El Niño event. By employing multitemporal Landsat data, these indices were computed to evaluate their capacity to capture both the spatial extent and severity of drought. The findings reveal notable temporal and spatial variations among the indices. The VCI, which primarily reflects vegetation health, exhibited greater sensitivity during the wet season (January-May), whereas the TCI, which assesses temperature-induced stress, identified larger drought areas in the dry season (August-November). The VHI, a composite index integrating both TCI and VCI, demonstrated balanced drought extent patterns. This study underscores that each index possesses unique strengths, rendering them complementary tools for drought monitoring in complex climatic regions such as Tehran. Understanding the distinctions among these indices can enhance the accuracy and applicability of information for drought management and policy formulation.

Keywords : Drought Monitoring, Remote Sensing, Temperature Condition Index (TCI), Vegetation Condition Index (VCI), Vegetation Health Index (VHI), El Niño, Tehran, Landsat.

INTRODUCTION

Droughts are among the most severe and complex natural hazards, affecting millions of people globally each year. They lead to devastating consequences for agriculture, water resources, and ecosystem health. The socioeconomic impacts of droughts are significant, causing agricultural production losses, water shortages, degradation of land, and forest fires. These conditions can trigger migration, disrupt livelihoods, and lead to conflicts over dwindling natural resources (Mehdipour et al., 2022; Anderson et al., 2021; Vicente-Serrano et al., 2020; Amalo et al., 2018; Mukherjee et al., 2018; Eslamian et al., 2017; Su et al., 2017; Dalezios et al., 2014). Therefore, timely and accurate drought monitoring is essential to mitigate the effects of drought and manage water and land resources effectively (Crespo et al., 2024; Son et al., 2021; Tramblay et al., 2020; Chuah et al., 2018).

Traditionally, drought has been monitored using in-situ data, such as rainfall, soil moisture, and temperature records. While these datasets are valuable, they are often spatially and temporally limited, making it difficult to assess drought conditions across large regions or rapidly changing climates. In recent years, remote sensing technologies have become a key tool for monitoring droughts due to their ability to provide near-real-time information across vast areas (Jiao et al., 2021; Jiao et al., 2020). Remote-sensing-based drought indices can offer continuous, spatially comprehensive data that are particularly useful in regions with sparse meteorological networks (McEvoy et al., 2020; Hazaymeh & Hassan, 2016; AghaKouchak et al., 2015).

Several remote-sensing drought indices have been developed to track drought conditions, including the Normalized Difference Vegetation Index (NDVI), Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI). These indices rely on satellite data to monitor the condition of vegetation and surface temperatures, which are important indicators of drought severity. The NDVI has been widely used for monitoring vegetation health, but more refined indices such as TCI, VCI, and VHI provide

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additional insights by incorporating land surface temperature (Bhuiyan et al., 2021; Xue & Su, 2017; Houborg et al., 2015; Jones & Vaughan, 2010).

The Temperature Condition Index (TCI) assesses drought by analyzing land surface temperature anomalies. High temperatures, particularly during dry seasons, can exacerbate vegetation stress and lead to severe drought conditions. TCI provides valuable insights into heat stress and is particularly useful for identifying drought during hot, dry periods (Yoon et al., 2020; Rembold et al., 2016). The Vegetation Condition Index (VCI), on the other hand, focuses on vegetation health by tracking changes in vegetation greenness. It is particularly sensitive to vegetation stress caused by droughts and is commonly used to monitor the health of crops and forests during periods of low precipitation (West et al., 2019).

The Vegetation Health Index (VHI) is a composite index that integrates both TCI and VCI, providing a more comprehensive understanding of drought dynamics by accounting for both temperature and vegetation stress. By combining these two factors, VHI is capable of offering more nuanced insights into drought severity, making it a valuable tool for monitoring drought in regions with complex climatic patterns (Alahacoon & Edirisinghe, 2022; Gxokwe et al., 2020; Tehrany et al., 2020). Additionally, Zarei (2022) assessed drought severity in western and northwestern Iran, finding PET as the main influence on SPEI, while temperature and precipitation-PET interactions were key factors for RDI across monthly and seasonal scales. Mohammadrezaei et al. (2020) examined the relationship between ocean-atmospheric indices and drought in Iran using over 30 years of precipitation data. They found that the Atlantic Multi-Decadal Oscillation (AMO) and NINO 4 had the strongest correlations with the Standard Precipitation Index (SPI), particularly in western and northern regions. The study highlights AMO's potential for improving drought prediction and management in Iran. Amini et al. (2020) applied Bayesian quantile regression to explore the impact of oceanic–atmospheric indices on drought in Iran. They found La Niña events intensified drought, especially in western, Caspian, and southern regions, while MEI positively influenced drought severity in low SPI quantiles. NAO showed minimal impact across regions and conditions. Tosunoglu et al. (2018) analyzed the spatial and temporal relationships between major atmospheric oscillations (NAO, SO, and NCP) and meteorological drought in Turkey using SPI data from 148 stations. They found that NAO and NCP influence drought conditions in western, central, northern, and eastern Turkey, with the strongest correlations at lag-0 for NAO and NCP, while SOI impacted SPI primarily with a 1–2 month lag.

Tehran, located in a semi-arid region, has experienced severe drought conditions in recent decades. The 2015 El Niño event was particularly impactful, bringing significant climatic anomalies that exacerbated drought conditions in the region. This study aims to evaluate the effectiveness of TCI, VCI, and VHI in monitoring drought conditions in Tehran during this period. By systematically comparing the spatial and temporal differences in drought extent captured by these indices, this research seeks not only to enhance existing drought monitoring methodologies but also to introduce a novel integrated framework that combines these indices for improved drought assessment. This innovative approach aims to provide a more holistic understanding of drought dynamics, ultimately contributing to the development of more effective drought management strategies and policy formulations tailored to the specific climatic challenges faced by Tehran.

METHODOLOGY

Study Area and Data Sources

Tehran, the capital of Iran, is located in a semi-arid region characterized by dry summers and mild, wet winters. Agriculture is a major economic activity in this region, making it vulnerable to drought conditions. The focus of this study is the year 2015, which coincided with one of the strongest El Niño events in recorded history (Timmermann et al., 2018). This event resulted in significant anomalies in temperature and precipitation, leading to drought conditions across the region.

To analyze drought conditions in Tehran, multitemporal Landsat data were obtained from the U.S. Geological Survey (USGS). Landsat provides high-resolution imagery that is widely used for environmental monitoring, including vegetation health and land surface temperature assessments. The data cover the entire year of 2015, allowing for a detailed analysis of drought conditions throughout both wet and dry seasons.

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Figure 1. (Upper panel) Position of study area, (Lower panel) Tehran 2017 map.

Drought Indices

In this study, three drought indices—Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI)—were calculated using Landsat data. Each index captures different aspects of drought severity and provides insights into the spatial and temporal patterns of drought in Tehran.

Temperature Condition Index (TCI)

TCI is based on land surface temperature (LST) data and is calculated using the following formula (Tsiros et al., 2004):

$$TCI = \frac{iLST\max - LST}{\min LST\max - LST} \times 100 \qquad (1)$$

In this equation, iLST represents the land surface temperature for the current month, while maxLST and minLST are the maximum and minimum LST values over a multi-year period. TCI values range from 0 to 100, with lower values indicating more severe drought conditions.

Vegetation Condition Index (VCI)

VCI is derived from the Enhanced Vegetation Index (EVI), which improves upon the traditional NDVI by correcting for atmospheric effects. It is calculated using the following formula (Quiring & Ganesh, 2010):

$$VCI = \frac{minEVI_i - EVI}{minLST_{max} - EVI} \times 100 \qquad (2)$$

Here, iEVI indicates the current vegetation condition, while maxEVI and minEVI are the multi-year maximum and minimum values of EVI. Similar to TCI, VCI values range from 0 to 100, with lower values indicating more severe vegetation stress.

Vegetation Health Index (VHI)

VHI combines both TCI and VCI to provide a more holistic view of drought severity. The formula for calculating VHI is as follows (Bento et al., 2018):

$$VHI = (VCI + TCI) \times 0.5 \qquad (3)$$

This composite index integrates both temperature and vegetation data, offering a comprehensive picture of drought conditions, making it particularly valuable for monitoring drought in regions with complex climatic patterns.

Analysis and Classification

The drought indices, TCI, VCI, and VHI, were computed for each month of 2015 to effectively capture seasonal variations in drought conditions across Tehran. This monthly calculation allows for a more nuanced understanding of how drought severity fluctuates with changes in climate and environmental factors throughout the year. By employing these indices, we can gain insights into both short-term drought events and longer-term trends, which are crucial for effective water resource management and agricultural planning in a region vulnerable to drought.

To classify the drought conditions, the calculated index values were categorized into five distinct severity classes: no drought, mild drought, moderate drought, severe drought, and extreme drought. This classification framework is critical for translating the index values into actionable insights for policymakers, agricultural stakeholders, and water management authorities. The spatial extent of drought was mapped using Geographic Information System (GIS) software, providing a detailed visualization of the temporal and spatial dynamics of drought across Tehran. This mapping process not only highlights the areas most affected by drought but also assists in identifying regions that may be more resilient or vulnerable to changing climatic conditions.

The classification of drought severity is outlined in **Table 1**, which delineates the criteria for each severity class. Values below 10 indicate extreme drought, while values ranging from 10 to 20 and 20 to 30 correspond to severe and moderate drought conditions, respectively. Mild drought is categorized for values below 40, and values above 40 are interpreted as no drought conditions. This classification enables a systematic approach to assess drought impacts and facilitates effective communication among stakeholders.

Table 1. Drought severity classes for TCI, VCI, and VHI.

Severity class	Values
Extereme Drought	< 10
Severe Drought	< 20
Moderate Drought	< 30
Mild Drought	< 40
No Drought	> 40

The analysis of the indices reveals distinct patterns of drought severity across the months of 2015. For instance, during the dry summer months, the indices typically showed heightened drought severity, aligning with the anticipated climatic conditions of Tehran. Conversely, the wet winter months tended to exhibit lower drought severity, demonstrating the natural seasonal fluctuations influenced by precipitation patterns.

By employing GIS technology to visualize these variations, the study not only illustrates the temporal progression of drought but also highlights critical geographic disparities within Tehran. Certain areas, particularly those with less vegetation cover or poor soil moisture retention, are likely to experience more severe drought conditions. Understanding these spatial dynamics is crucial for developing targeted intervention strategies to mitigate the adverse effects of drought on agriculture, water resources, and overall ecosystem health.

In conclusion, the classification and analysis of the drought indices underscore the importance of continuous monitoring and assessment of drought conditions. By integrating advanced remote sensing techniques with robust statistical analysis, this study contributes valuable insights into the evolving nature of drought in Tehran, facilitating informed decision-making and enhanced resilience against future drought events.

RESULTS AND DISCUSSION

Variability in Drought Conditions: Insights from VCI, TCI, and VHI Indices

The findings of this study highlight significant variability in drought areal extent and severity, as evidenced by the three indices analyzed.

Vegetation Condition Index (VCI)

The VCI demonstrated a pronounced drought areal extent during the wet months from January to May. This sensitivity to changes in vegetation health during the critical agricultural period indicates that the VCI is particularly adept at detecting vegetation stress linked to reduced precipitation. Such insights are essential for evaluating the impact of drought on agricultural productivity (West et al., 2019; Jiao et al., 2020). As shown in **Figure 2**, the VCI values from September 2017 reflect these conditions, providing a visual representation of drought impacts on vegetation health.

Temperature Condition Index (TCI)

In contrast, the TCI exhibited a higher drought areal extent during the dry months of August to November. This index is responsive to temperature anomalies, and the dry season in Tehran is characterized by elevated temperatures that intensify vegetation stress. The TCI effectively captured this temperature-induced stress, thereby proving to be a valuable tool for monitoring drought during periods of extreme heat (Liu et al., 2021; Vicente-Serrano et al., 2015). **Figure 3** illustrates the TCI values for October 2013 and 2001, highlighting the drought severity during those dry months.

Vegetation Health Index (VHI)

The VHI, which integrates both TCI and VCI, presented an intermediate drought areal extent throughout the year. This index provides a balanced representation of drought conditions by accounting for both temperature-induced and vegetation-based factors. The VHI's ability to combine the strengths of TCI and VCI renders it a useful instrument for comprehensive drought assessment, particularly in regions experiencing variable climatic conditions (Alahacoon & Edirisinghe, 2022; Wei et al., 2021; Mansour Badamassi et al., 2020). The integration of VHI in the analysis provides further insights into the drought conditions depicted in both **Figures 2 and 3**.

Figure 2. Drought map of September 2017 using (a) TCI, (b) VCI and (c) VHI.

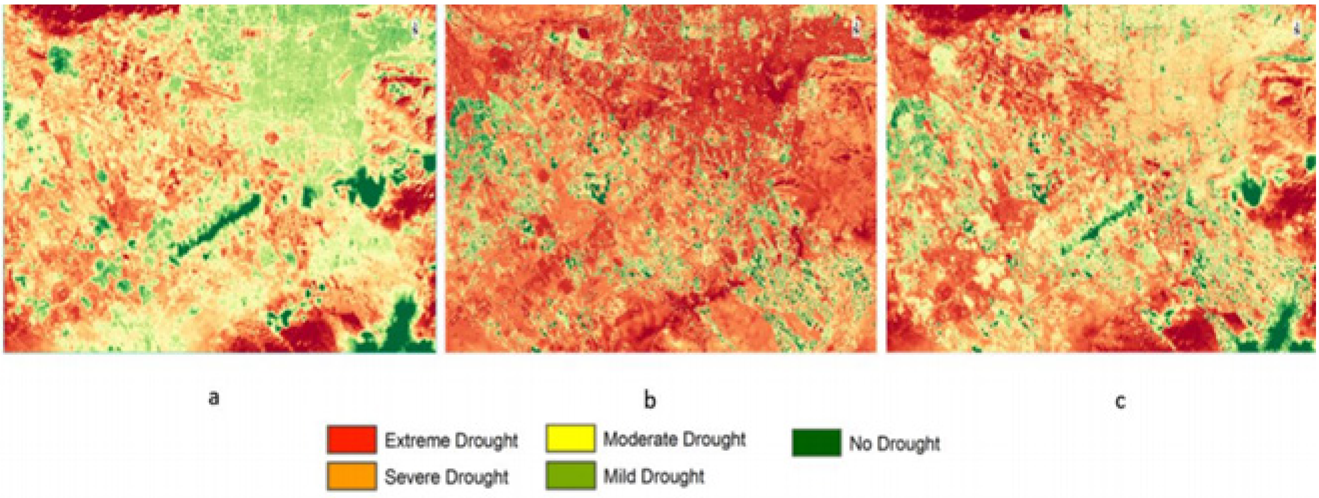
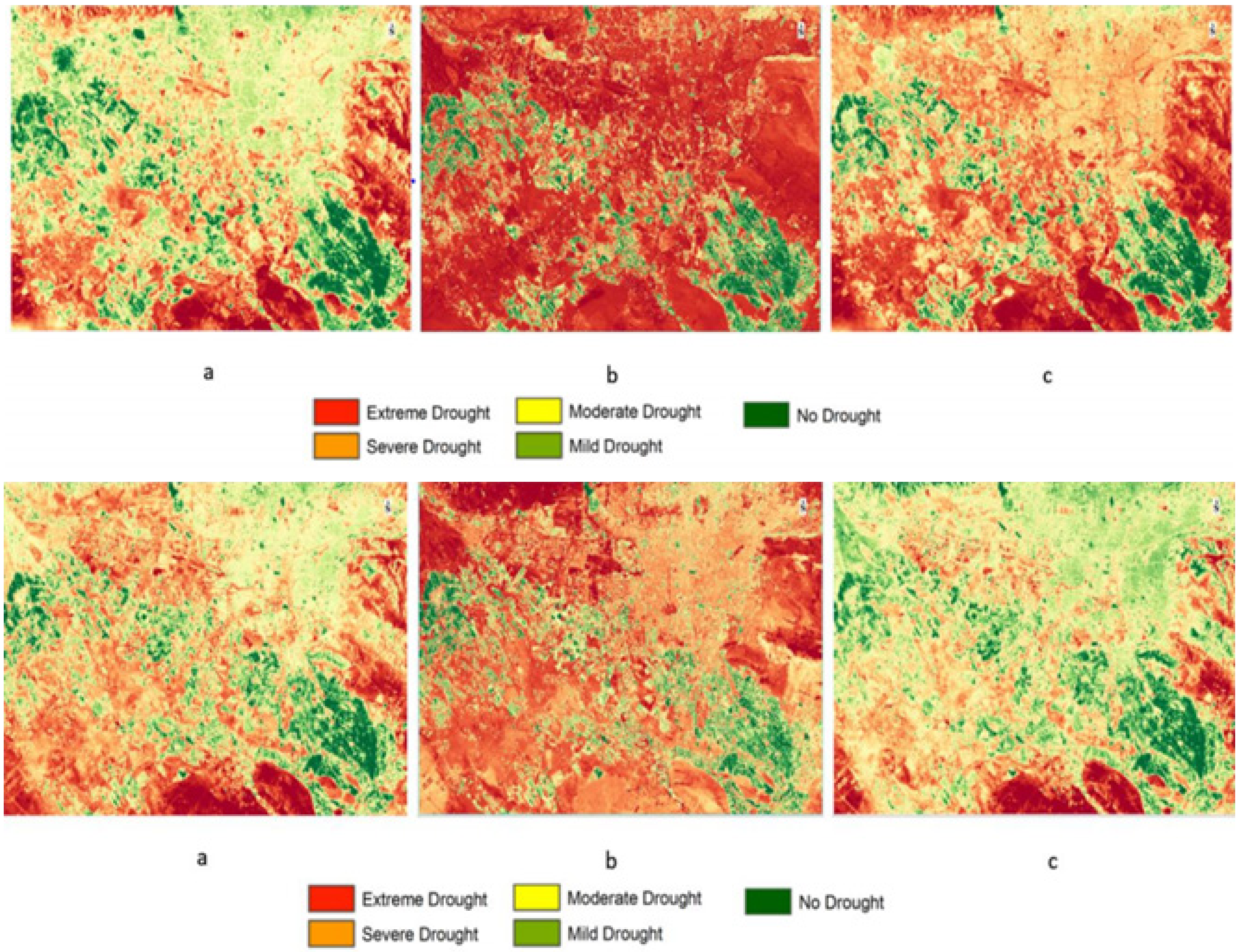


Figure 3. Drought map of October 2013 and 2001 using (a) TCI, (b) VCI and (c) VHI.



Patterns of Drought Severity in Tehran: Analysis Using VCI and TCI

The classification of drought severity revealed distinct patterns of drought conditions across Tehran, particularly in the months of November during the years 1980 and 1990, as illustrated in **Figure 4**.

Vegetation Condition Index (VCI): The VCI indicated healthier vegetation during the wet seasons, as reflected by higher VCI values. This observation underscores the positive impacts of increased precipitation on plant health. However, in the context of drought severity, the VCI also identified extreme drought conditions in agricultural areas during critical periods, such as harvest time, highlighting the vulnerabilities of these regions to climatic stressors.

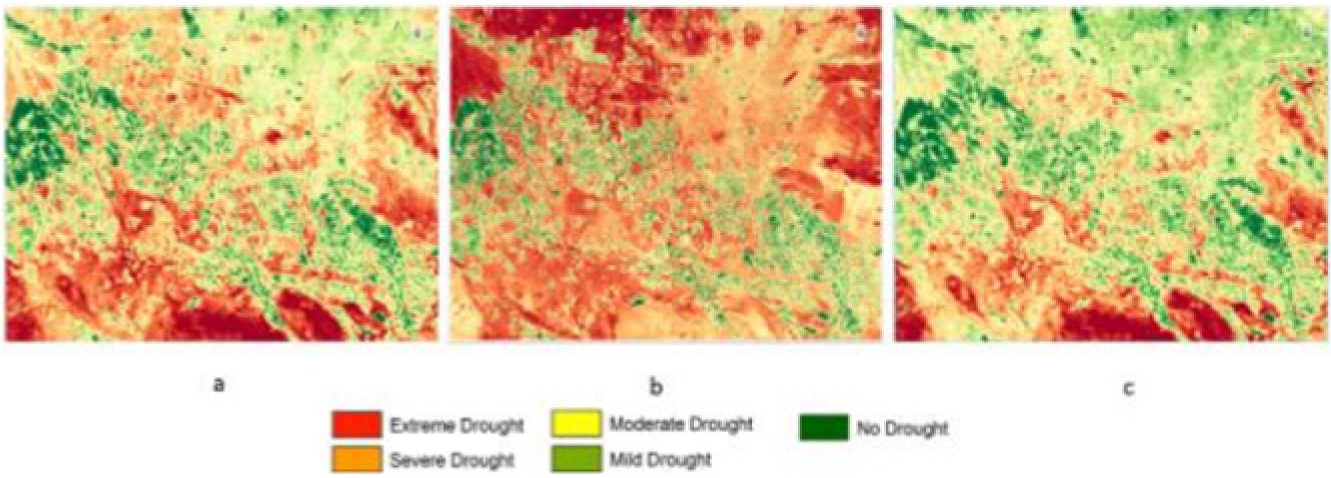
Temperature Condition Index (TCI): In contrast, the TCI exhibited greater variability during the dry seasons of these years, demonstrating its sensitivity to temperature fluctuations. The analysis revealed that regions most affected by drought often corresponded with areas experiencing extreme temperature anomalies. This finding emphasizes the need for integrative approaches that utilize multiple indices for effective drought monitoring (Shukla et al., 2021).

Spatial Distribution of Drought Severity: The spatial distribution of drought severity classes varied significantly across the two months analyzed. For instance, the TCI detected severe drought conditions in urban areas during heat waves, while the VCI reflected extreme drought in agricultural regions. Such findings underscore the importance of context when interpreting remote sensing data, as different ecosystems—agricultural, urban, and natural—respond uniquely to climatic stressors (Smith et al., 2014; Lassalle, 2021).

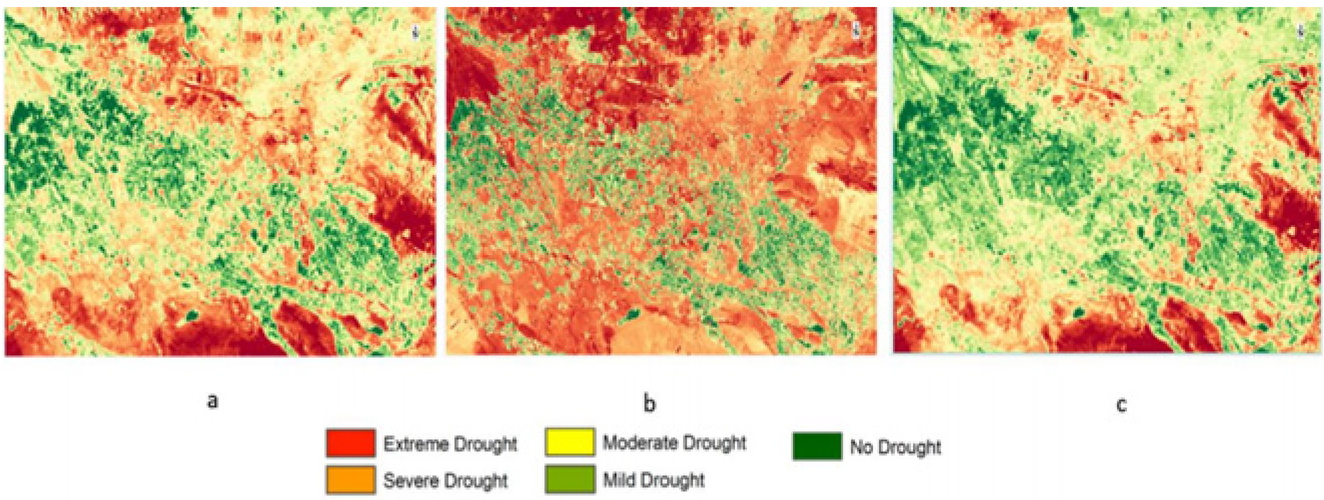
Figure 4 illustrates the drought maps for November 1990 and 1980, showcasing the variations in drought severity as determined by (a) TCI, (b) VCI, and (c) VHI. These maps provide valuable insights into the climatic challenges faced during these periods, further highlighting the importance of using multiple indices for a comprehensive assessment of drought conditions.

Figure 4. Drought map of November 1990 and 1980 using (a) TCI, (b) VCI and (c) VHI.

1990



1980



Leveraging the Strengths of VCI and TCI for Comprehensive Drought Monitoring

The comparative analysis of the indices underscored the unique strengths of each, demonstrating that their combined application could yield a significantly more comprehensive assessment of drought conditions. The Vegetation Condition Index (VCI) excels in its sensitivity to changes in vegetation health, enabling the early identification of potential crop failures. This early warning capability is crucial for agricultural management, allowing for timely interventions that could mitigate losses.

Conversely, the Temperature Condition Index (TCI) focuses on temperature anomalies, providing critical insights into heat-related stress that may not be adequately captured by vegetation-based indices alone (Zhang et al., 2021).

Integrating these indices can enhance our understanding of the complex interplay between vegetation health and climatic factors, thereby fostering more effective drought monitoring and response strategies. Future research endeavors could investigate the development of hybrid indices that merge the strengths of the TCI, VCI, and Vegetation Health Index (VHI). Such innovations would facilitate a more nuanced understanding of drought dynamics and significantly improve the accuracy of drought predictions, ultimately aiding in better resource management and policy formulation.

CONCLUSION

This study elucidates the distinctive advantages of the Temperature Condition Index (TCI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI) in monitoring drought conditions in Tehran during the 2015 El Niño event. The results indicate that the VCI is particularly effective in identifying vegetation stress during periods of increased precipitation, thereby serving as a crucial tool for assessing plant health and potential agricultural impacts. Conversely, the TCI demonstrates superior efficacy in capturing temperature-induced drought conditions during arid months, highlighting its relevance in understanding the thermal stress effects on vegetation.

The VHI functions as a valuable composite metric, synthesizing the strengths of both the VCI and TCI to provide a comprehensive assessment of drought dynamics. This analysis underscores the necessity of selecting appropriate indices that align with specific climatic contexts and research objectives, reinforcing the idea that a one-size-fits-all approach may be inadequate for effective drought monitoring.

Moreover, the integration of multiple remote-sensing indices can substantially enhance the capabilities of drought assessment, facilitating the development of more robust management strategies in response to climate variability. As global drought conditions increasingly threaten agricultural productivity and water resources, ongoing research aimed at refining remote-sensing methodologies and indices is imperative. Future investigations should also focus on incorporating additional variables, such as soil moisture content and precipitation forecasting, to augment the predictive accuracy of drought models.

REFERENCES

1. AghaKouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D., & Hain, C. R. (2015). Remote sensing of drought: Progress, challenges and opportunities. Reviews of Geophysics, 53(2), 452-480.

2. Alahacoon, N., & Edirisinghe, M. (2022). A comprehensive assessment of remote sensing and traditional based drought monitoring indices at global and regional scale. Geomatics, Natural Hazards and Risk, 13(1), 762-799.

3. Amalo, L. F., Hidayat, R., & Sulma, S. (2017). Analysis of agricultural drought in east java using vegetation health index. AGRIVITA, Journal of Agricultural Science, 40(1), 63-73.

4. Amini, M., Ghadami, M., Fathian, F., & Modarres, R. (2020). Teleconnections between oceanic–atmospheric indices and drought over Iran using quantile regressions. Hydrological Sciences Journal, 65(13), 2286-2295.

5. Anderson, W., Taylor, C., McDermid, S., Ilboudo-Nébié, E., Seager, R., Schlenker, W., ... & Markey, K. (2021). Violent conflict exacerbated drought-related food insecurity between 2009 and 2019 in sub-Saharan Africa. Nature Food, 2(8), 603-615.

6. Bento, V. A., Gouveia, C. M., DaCamara, C. C., & Trigo, I. F. (2018). A climatological assessment of drought impact on vegetation health index. Agricultural and forest meteorology, 259, 286-295.

7. Chuah, C. J., Ho, B. H., & Chow, W. T. (2018). Trans-boundary variations of urban drought vulnerability and its impact on water resource management in Singapore and Johor, Malaysia. Environmental Research Letters, 13(7), 074011.

8. Crespo, N., Pádua, L., Santos, J. A., & Fraga, H. (2024). Satellite Remote Sensing Tools for Drought Assessment in Vineyards and Olive Orchards: A Systematic Review. Remote Sensing, 16(11), 2040.

9. Dalezios, N. R., Blanta, A., Spyropoulos, N. V., & Tarquis, A. M. (2014). Risk identification of agricultural drought for sustainable agroecosystems. Natural Hazards and Earth System Sciences, 14(9), 2435-2448.

10. Eslamian, S., Ostad-Ali-Askari, K., Singh, V. P., Dalezios, N. R., Ghane, M., Yihdego, Y., & Matouq, M. (2017). A review of drought indices. Int. J. Constr. Res. Civ. Eng, 3(4).

11. Gxokwe, S., Dube, T., & Mazvimavi, D. (2020). Multispectral remote sensing of wetlands in semi-arid and arid areas: a review on applications, challenges and possible future research directions. Remote Sensing, 12(24), 4190.

12. Hazaymeh, K., & Hassan, Q. K. (2016). Remote sensing of agricultural drought monitoring: A state of art review. AIMS Environmental Science, 3(4), 604-630.

13. Houborg, R., Fisher, J. B., & Skidmore, A. K. (2015). Advances in remote sensing of vegetation function and traits. International Journal of Applied Earth Observation and Geoinformation, 43, 1-6.

14. Jiao, W., Wang, L., & McCabe, M. (2020, December). Multi-sensor remote sensing for drought characterization. In AGU Fall Meeting Abstracts (Vol. 2020, pp. H122-04).

15. Jiao, W., Wang, L., & McCabe, M. F. (2021). Multi-sensor remote sensing for drought characterization: current status, opportunities and a roadmap for the future. Remote Sensing of Environment, 256, 112313.

16. Jones, H. G., & Vaughan, R. A. (2010). Remote sensing of vegetation: principles, techniques, and applications. Oxford University Press, USA.

17. Lassalle, G. (2021). Monitoring natural and anthropogenic plant stressors by hyperspectral remote sensing: Recommendations and guidelines based on a meta-review. Science of the Total Environment, 788, 147758.

18. Liu, L., Huang, R., Cheng, J., Liu, W., Chen, Y., Shao, Q., ... & Huang, J. (2021). Monitoring meteorological drought in southern China using remote sensing data. Remote Sensing, 13(19), 3858.

19. Mansour Badamassi, M. B., El-Aboudi, A., & Gbetkom, P. G. (2020). A new index to better detect and monitor agricultural drought in Niger using multisensor remote sensing data. The Professional Geographer, 72(3), 421-432.

20. Mehdipour, S., Nakhaee, N., Khankeh, H., & Haghdoost, A. A. (2022). Impacts of drought on health: A qualitative case study from Iran. International Journal of Disaster Risk Reduction, 76, 103007.

21. Mohammadrezaei, M., Soltani, S., & Modarres, R. (2020). Evaluating the effect of ocean-atmospheric indices on drought in Iran. Theoretical and Applied Climatology, 140, 219-230.

22. Mukherjee, S., Mishra, A., & Trenberth, K. E. (2018). Climate change and drought: a perspective on drought indices. Current climate change reports, 4, 145-163.

23. Quiring, S. M., & Ganesh, S. (2010). Evaluating the utility of the Vegetation Condition Index (VCI) for monitoring meteorological drought in Texas. Agricultural and forest meteorology, 150(3), 330-339.

24. Rembold, F., Meroni, M., Atzberger, C., Ham, F., Fillol, E., & Thenkabail, P. S. (2016). Agricultural drought monitoring using space-derived vegetation and biophysical products: a global perspective. Remote Sensing Handbook, 3, 349-365.

25. Shukla, S., Husak, G., Turner, W., Davenport, F., Funk, C., Harrison, L., & Krell, N. (2021). A slow rainy season onset is a reliable harbinger of drought in most food insecure regions in Sub-Saharan Africa. Plos one, 16(1), e0242883.

26. Smith, A. M., Kolden, C. A., Tinkham, W. T., Talhelm, A. F., Marshall, J. D., Hudak, A. T., ... & Gosz, J. R. (2014). Remote sensing the vulnerability of vegetation in natural terrestrial ecosystems. Remote sensing of environment, 154, 322-337.

27. Son, B., Im, J., Park, S., & Lee, J. (2021). Satellite-based Drought Forecasting: Research Trends, Challenges, and Future Directions. Korean Journal of Remote Sensing, 37(4), 815-831.

28. Su, Z., He, Y., Dong, X., & Wang, L. (2017). Drought monitoring and assessment using remote sensing. Remote sensing of hydrological extremes, 151-172.

29. Timmermann, A., An, S. I., Kug, J. S., Jin, F. F., Cai, W., Capotondi, A., ... & Zhang, X. (2018). El Niño–southern oscillation complexity. Nature, 559(7715), 535-545.

30. Tosunoglu, F., Can, I., & Kahya, E. (2018). Evaluation of spatial and temporal relationships between large-scale atmospheric oscillations and meteorological drought indexes in Turkey. International Journal of Climatology, 38(12), 4579-4596.

31. Tramblay, Y., Koutroulis, A., Samaniego, L., Vicente-Serrano, S. M., Volaire, F., Boone, A., ... & Polcher, J. (2020). Challenges for drought assessment in the

Mediterranean region under future climate scenarios. Earth-Science Reviews, 210, 103348.

32. Tsiros, E., Domenikiotis, C., Spiliotopoulos, M., & Dalezios, N. R. (2004, September). Use of NOAA/AVHRR-based vegetation condition index (VCI) and temperature condition index (TCI) for drought monitoring in Thessaly, Greece. In EWRA Symposium on water resources management: risks and challenges for the 21st century, Izmir, Turkey (pp. 2-4).

33. Vicente-Serrano, S. M., Cabello, D., Tomás-Burguera, M., Martín-Hernández, N., Beguería, S., Azorin-Molina, C., & El Kenawy, A. (2015). Drought variability and land degradation in semiarid regions: Assessment using remote sensing data and drought indices (1982–2011). Remote Sensing, 7(4), 4391-4423.

34. Vicente-Serrano, S. M., McVicar, T. R., Miralles, D. G., Yang, Y., & Tomas-Burguera, M. (2020). Unraveling the influence of atmospheric evaporative demand on drought and its response to climate change. Wiley Interdisciplinary Reviews: Climate Change, 11(2), e632.

35. Wei, W., Zhang, J., Zhou, L., Xie, B., Zhou, J., & Li, C. (2021). Comparative evaluation of drought indices for monitoring drought based on remote sensing data. Environmental Science and Pollution Research, 28, 20408-20425.

36. West, H., Quinn, N., & Horswell, M. (2019). Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. Remote Sensing of Environment, 232, 111291.

37. Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. Journal of sensors, 2017(1), 1353691.

38. Yoon, D. H., Nam, W. H., Lee, H. J., Hong, E. M., Feng, S., Wardlow, B. D., ... & Kim, D. E. (2020). Agricultural drought assessment in East Asia using satellite-based indices. Remote Sensing, 12(3), 444.

39. Zarei, A. R. (2022). Assessing the importance of climate variables on RDI and SPEI using backward multiple linear regression in arid to humid regions over Iran. Pure and Applied Geophysics, 179(8), 2905-2921.