

Using Landsat Satellite Data to Explore Drought Index during the Dry Season Period 1990–2024 in Thu Duc City of Ho Chi Minh City, Vietnam

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Abstract

Drought is among the most significant natural disasters globally, caused by prolonged rainfall deficits that result in precipitation levels significantly below the long-term average. It has far-reaching impacts on the environment, economy, and society, including reduced agricultural productivity, diminished arable land, and socio-economic challenges. In recent years, remote sensing has emerged as a powerful tool for drought monitoring and mapping, offering significant advantages in spatial and temporal analysis. This study aimed to assess drought trends in Thu Duc City, Ho Chi Minh City, Vietnam, during the dry seasons from 1990 to 2024 using Landsat satellite data processed on the Google Earth Engine platform. The Normalized Difference Drought Index (NDDI), derived from the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI), was utilized to quantify drought severity. The results indicate a substantial increase in drought-affected areas over the study period, particularly after 2000, with drought severity closely linked to El Niño-Southern Oscillation (ENSO) cycles. Areas with low vegetation and water content were most vulnerable to high drought levels, as reflected in NDDI values. Notably, the northern and southern regions of Thu Duc City exhibited frequent drought occurrences, while areas with dense vegetation and abundant water resources, such as the eastern parts, were less affected. To further validate these findings, a land cover classification provided the relationship between drought-prone areas and different land cover types, highlighting the role of urban expansion and vegetation loss in increasing drought susceptibility. Urbanized areas exhibited higher drought intensity, whereas regions with substantial green cover and water bodies showed lower drought impact. Future studies should collect more field data to enhance the reliability of drought assessments. Expanding the temporal and spatial scope and examining socio-economic impacts will provide a more comprehensive understanding of drought dynamics. These findings underscore the importance of remote sensing in supporting sustainable urban planning and resource management in newly established urban areas as Thu Duc City.

Keywords: Drought, ENSO, NDDI, NDVI, NDWI

1. Introduction

Drought is one of the most prevalent natural challenges worldwide, significantly affecting the environment and human production activities. Globally, in terms of property damage and loss of life, drought ranks fourth, following floods, earthquakes, and storms. Extreme drought episodes have become more frequent and severe in recent years, causing major ecological disruption, environmental deterioration, and decreased agricultural productivity [1] and [2]. A typical drought occurrence physically appears as a protracted shortage of water flux and storage, which can upset

established hydrological balances [3]. Drought is classified into four main types: meteorological drought, hydrological drought, agricultural drought, and socio-economic drought, each with its own unique characteristics and consequences [4] and [5]. Traditionally, drought monitoring has primarily relied on ground-based meteorological stations. However, reality shows that installing monitoring stations for factors such as rainfall, humidity, temperature, etc. is often ineffective for drought surveys due to the requirement of a dense network, and installation costs are quite large.

The above mentioned stations are also not sufficient to capture the spatial and temporal variation of drought-related factors due to differences in data quality. These challenges force researchers to think about new approaches in drought research [6]. Remote sensing is a technology that enables data collection without direct contact with the subject, utilizing sensors to measure or detect various types of energy, such as electromagnetic radiation and acoustic signals, emitted, reflected, or scattered by the object under investigation [7] and [8].

Remote sensing enables the collection of Earth surface data over large areas, providing continuous and reliable information [9]. Globally, numerous studies have utilized integrated drought indices to assess and monitor drought conditions, yielding encouraging results in recent years [10][11] and [12]. In Vietnam, drought is one of the issues that receive the most research attention, in which the research direction of drought forecasting and drought assessment for prevention is prominent. The topic that receives the most research attention, which stands out is the research direction of drought forecasting and drought assessment to serve prevention work, many researchers have also

conducted significant studies in this field [9][13] and [14]. However, the previous research mostly studied large areas and rarely mentioned specific areas or cities.

The study area, Thu Duc City, is a newly established administrative unit formed in early 2021 by merging District 2, District 9, and the former Thu Duc District. The area features diverse topography, with an average elevation ranging from 5 meters to 25 meters, gradually sloping from north to south, and interspersed with major rivers and canals. Previously, no specific studies on drought have been conducted for Thu Duc City. Most prior research has focused on larger regional scales. Therefore, studying drought conditions in Thu Duc City is essential, particularly for a newly established city like Thu Duc. Such research is critical for urban management and future development planning [15]. In this study, the Normalized Difference Drought Index (NDDI) was employed to evaluate drought conditions in Thu Duc City from 1990 to 2024. The findings aim to provide a comprehensive understanding of drought trends in the area, supporting the development of effective resource management strategies and sustainable urban planning.

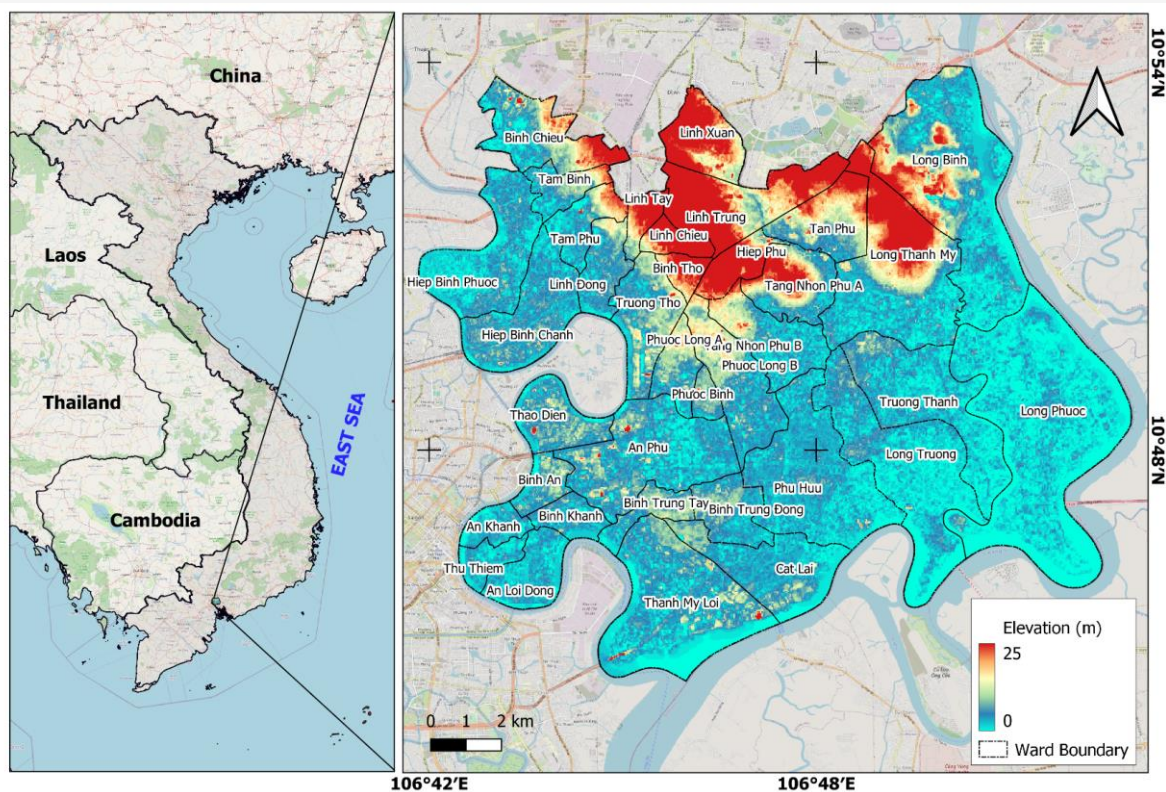


Figure 1: Administrative boundary of Thu Duc City, Vietnam

1.1 Data

1.1.1 Satellite data

The Landsat image datasets used for the research were acquired in the years: 1990, 1995, 2000, 2005, 2010, 2015, 2020, 2023, 2024. These datasets were processed from the Google Earth Engine (GEE) platform, which were standardized and synthesized according to the dry months (January to April) of the study years. All data was filtered using the `filterDate()` function on the Google Earth Engine (GEE) platform filtering from January 1 to April 30. GEE allows researchers to access a large repository of remote sensing imagery of various types, such as Landsat, Sentinel, MODIS, etc., with the latest data sources [16]. Landsat 5 and Landsat 8 are pivotal satellite missions providing essential remote sensing data. Landsat 5, launched in 1984, features six multi-spectral bands operating in visible and infrared wavelengths, all with a spatial resolution of 30 m, along with a thermal infrared band (Band 6) at a 120 m resolution to capture surface temperature. In contrast, Landsat 8, launched on February 11, 2013, enhances this capability with 11 spectral bands: eight multi-spectral bands at 30 m resolution, a panchromatic band (Band 8) at 15 m, and two thermal infrared bands (17 and 18) at a 100 m resolution. Together, these satellites offer valuable data for a range of applications, from land use monitoring to climate studies, reflecting advancements in remote sensing technology [17] and [18].

1.1.2 Land cover data

Additionally, land cover data was created by Ho Chi Minh City Space Technology Application Center (STAC), belonging to Vietnam National Space Center (VNSC) to assess the results. There are five Land cover maps of Thu Duc City in the years of 1990, 2000, 2008, 2015 and 2023. The maps were classified by annual Landsat satellite imageries using the Random Forest algorithm a machine learning method based on decision trees (Figure 1).

1.2 Method

In this study, the Normalized Difference Drought Index (NDDI) was selected to determine drought limit levels for periods of interest based on the drought threshold from the value range of NDDI. Areas with higher NDDI values show higher drought levels. The NDDI values are categorized as in Table 1. The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) are the two indices whose computation results determine the NDDI index. NDDI is defined in Equation 1[19].

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI}$$

Equation 1

The NDVI index is determined based on the different spectral reflectance of plants in the red and near-infrared bands. NDVI values range from -1 to 1, low NDVI values represent areas with low vegetation coverage. High NDVI values represent areas with high vegetation cover, negative NDVI represents moist soil and water areas [20] The vegetation density classified by NDVI is presented in Table 2).

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Equation 2

NDWI is based on the spectral reflection of the green band and the absorption characteristics of the short infrared band to the water surface object. NDWI value is between -1 and 1 and is classified as in Table 3. NDWI is calculated by Equation 3 [21].

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR}$$

Equation 3

Table 1: NDDI value classification [19]

NDDI value	Dryness class
≤ 0.0	No dryness
$0 < NDDI \leq 0.2$	Low
$0.2 < NDDI \leq 0.4$	Moderate
$0.4 < NDDI \leq 0.6$	High
> 0.6	Very high

Table 2: NDVI value classification [20]

NDVI	Vegetation density
≤ 0.2	Very low
$0.2 < NDVI \leq 0.4$	Low
$0.4 < NDVI \leq 0.8$	Moderate
> 0.8	High

Table 3: NDWI value classification [22]

NDWI value	Class
< 0.3	Dry/ no water
≥ 0.3	Wet/ water surface

The study process is shown in the diagram (Figure 2).

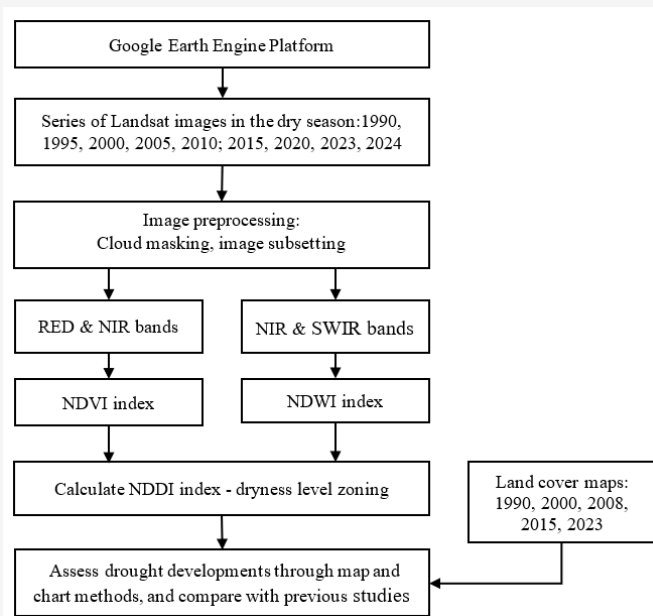


Figure 2: Workflow of the research implementation process

2. Results

2.1 Results of NDVI

The larger the areas of NDVI concentration, the higher the likelihood of plant presence. Overall, in the period 1990–2024, the rapid development of urbanization has caused vegetation to gradually decrease over time, so NDVI tends to decrease sharply over the years, especially in the period after 2000. This is most obvious in the Northwest areas of the city; some areas have had a sharp downward trend since 2000, such as Linh Xuan, Linh Trung, Linh Tay, Linh Chieu, Hiep Binh Chanh, Hiep Binh Phuoc, and Truong Tho. The Eastern side of the city has always had a plant presence; over the years this presence has decreased but not significantly. In the period 2023–2024, the area with the most concentrated vegetation density is in the East of the city, especially Long Phuoc. The decline of vegetation in the Northern and Northwest areas, Thu Duc will also increase the risk of drought in these areas (Figure 3). The area of the NDVI value ranges in the study area has changed significantly over the years. The NDVI primarily fluctuates between 0.2 and 0.8, with values greater than 0.8 appearing only in very small areas in the years 2000 and 2010, accounting for approximately 0.06% and 0.28%, respectively. At the same time, the proportion of NDVI area in the range below 0.2 has shown a rapid

increase since 2000, with the percentage of NDVI area in this range being 13.10% in 1990, approximately 13.57% in 2000, and then increasing rapidly thereafter. By 2024, this range accounts for 35.34%. Conversely, the NDVI range from 0.4 to 0.8 has shown a decreasing trend, especially after 2015, with the area percentages for the years 2015, 2020, 2023, and 2024 being 13.66%, 8.42%, 6.11%, and 6.5%, respectively. NDVI in the range of 0.2 to 0.4 occupies the largest area but shows almost no clear trend of change. The area percentage in 1990 was 66.15%, which decreased to about 43.67% by 2000. By 2015, the area percentage of NDVI in this range increased to 55.93% and has changed insignificantly in the following years (Figure 4).

2.2 Results of NDWI

The NDWI index is widely used in surface water monitoring from remote sensing data. Areas with higher NDWI values indicate the presence of water. Figure 5 shows areas with concentrated water in some areas such as at the boundary of Thu Duc City, which is home to many canals and large rivers, in wards on the Eastern, Western and Southern edges of the city, typically the Long Binh, Long Phuoc, Long Truong, Truong Thanh, Long Thanh My Phu Huu, Cat Lai, Thanh My Loi, Thao Dien Wards.

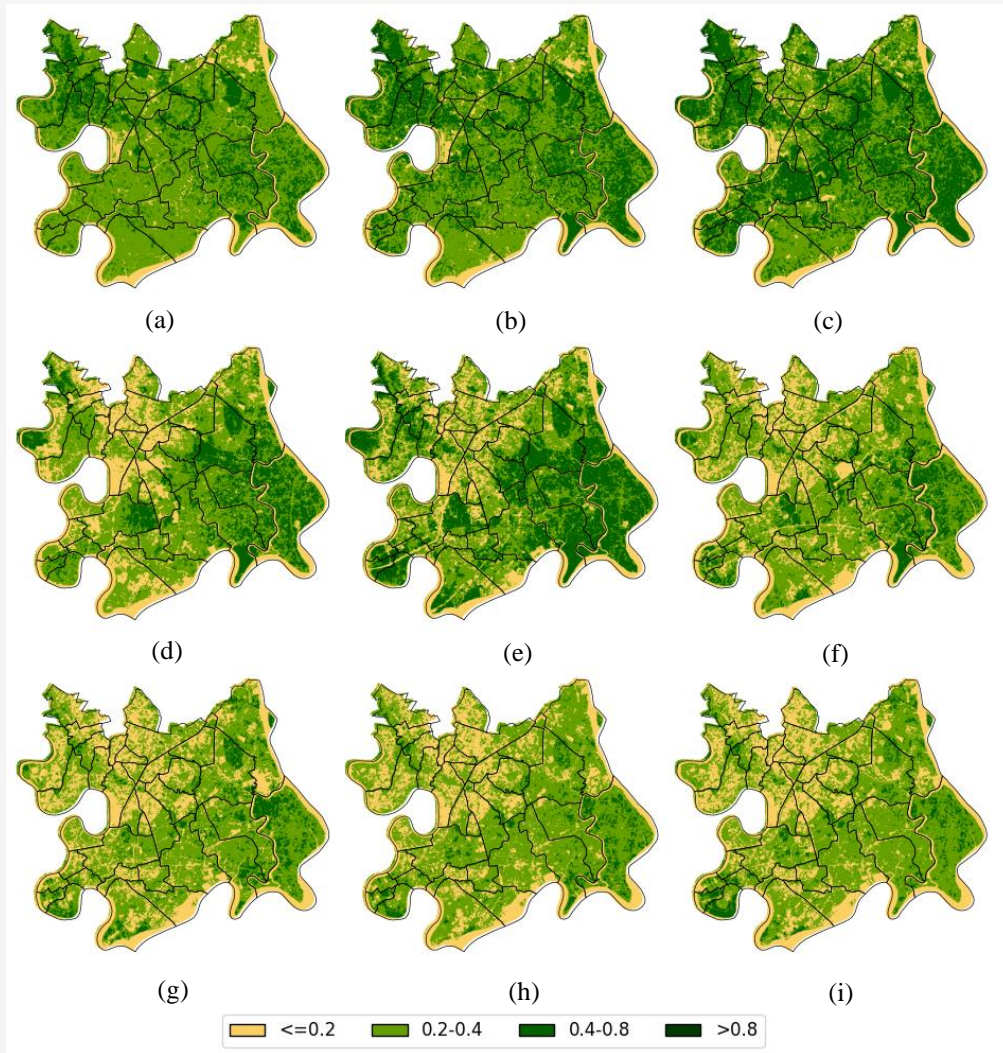


Figure 3: NDVI in dry season from 1990-2024 in Thu Duc City
 (a) 1990 (b) 1995 (c) 2000 (d) 2005 (e) 2010 (f) 2015 (g) 2020 (h) 2023 (i) 2024

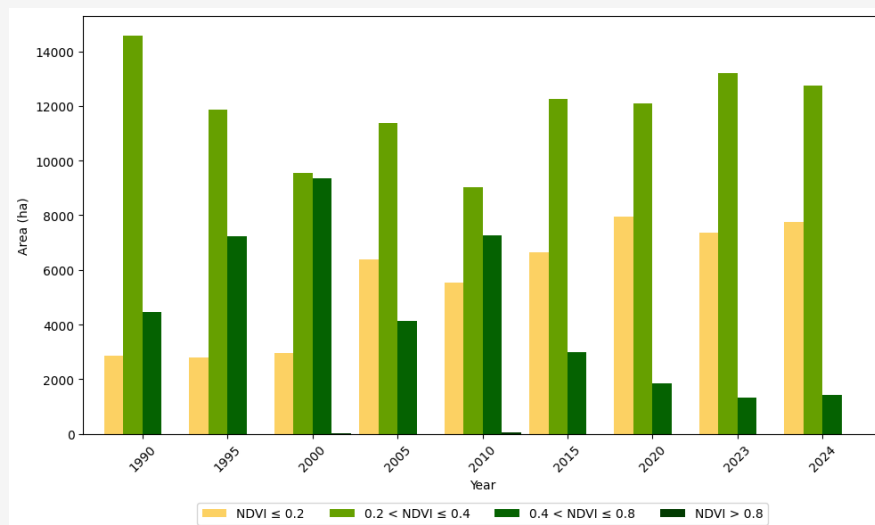


Figure 4: Temporal variation of area of NDVI ranges in dry season from 1990-2024 in Thu Duc City

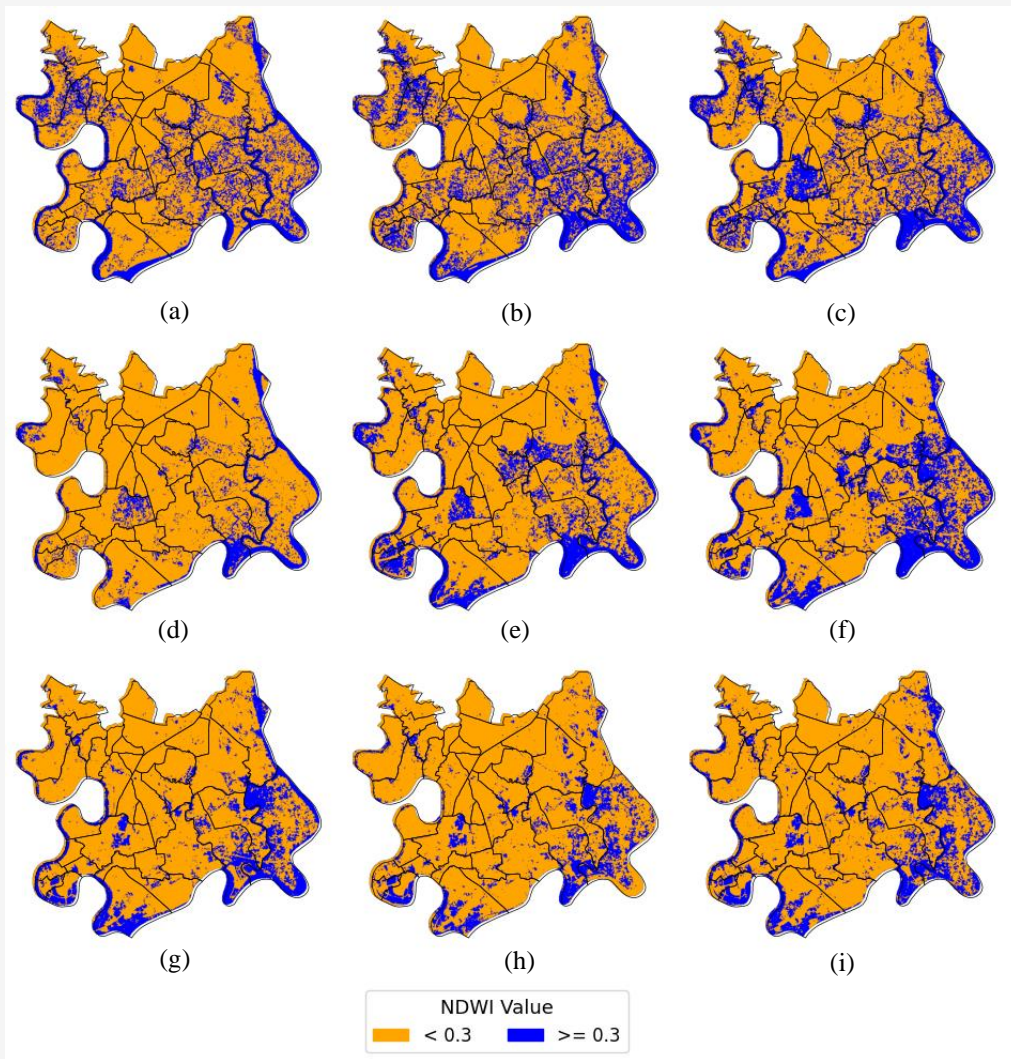


Figure 5: NDWI in dry season from 1990-2024 in Thu Duc City
 (a) 1990 (b)1995 (c) 2000 (d) 2005 (e) 2010 (f) 2015 (g) 2020 (h) 2023 (i) 2024

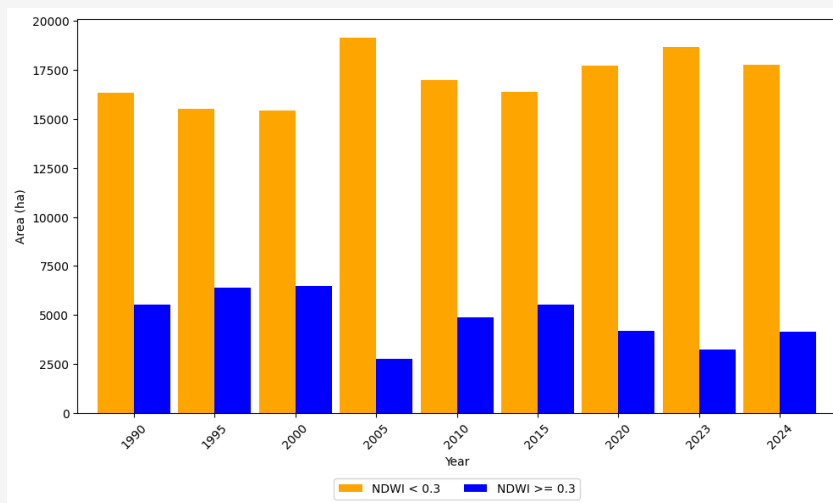


Figure 6: Temporal variation of area of NDWI ranges in dry season from 1990-2024 in Thu Duc City

The results in Figure 6, water/non-water areas do not change significantly from 1990 to 2024. At the value range of $NDWI < 0.3$, in 1990 the lowest area is about 74.67 %, in 2024 it is about 81.00 %, $NDWI \geq 0.3$ accounts for the lowest area in 2005 with 12.63%.

2.3 Results of NDDI

The distribution results of the NDDI value shows that drought has changed in both intensity and area in the years studied. Areas classified as high dryness ($0.4 < NDDI \leq 0.6$) and very high dryness ($NDDI > 0.6$) are primarily concentrated in regions with low NDVI and NDWI, while areas with low NDDI ($0,0 < NDDI \leq 0.2$) mainly focuses on areas with high NDVI and

NDWI values. The northern areas (Linh Xuan, Linh Trung, Binh Chieu, Tam Binh) and some southern areas (Thanh My Loi) frequently endure high levels of drought during the years studied. In the Eastern region, the Long Phuoc wards, which are less affected by drought, experienced unusually high levels of drought in 2010 and 2015. In the remaining years, the level of drought is lower and continues to trend upwards. an increasing trend in recent years (Figure 7). The data in Table 4 and Figure 8 shows that the changes in the area ratio of drought levels over the years of study. It is evident that the rate of drought severity, both high and very high, has a clear upward trend.

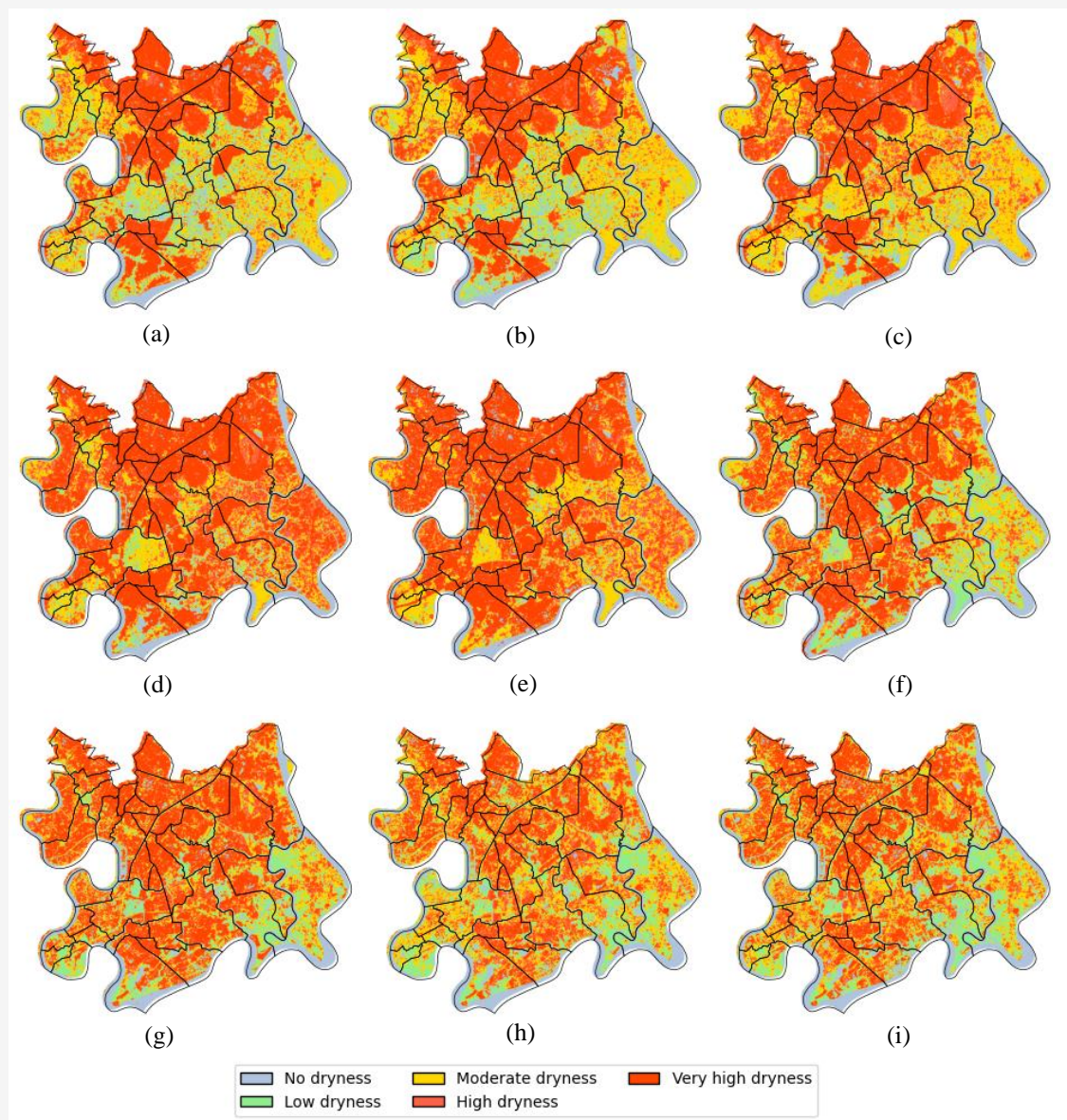


Figure 7: NDDI in dry season from 1990-2024 in Thu Duc City
(a) 1990 (b)1995 (c) 2000 (d) 2005 (e) 2010 (f) 2015 (g) 2020 (h) 2023 (i) 2024

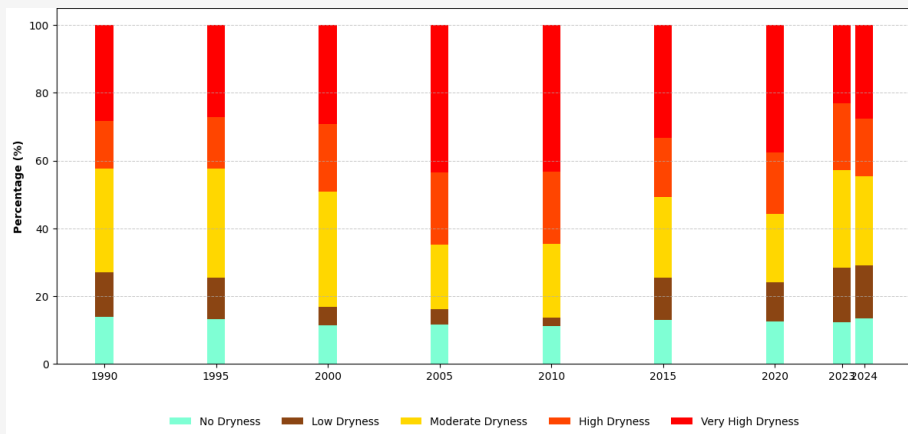


Figure 8: Temporal variation of area percentage of drought levels from 1990-2024 in Thu Duc City

Table 4: Distribution of area percentage of drought levels (%) from 1990-2024 in Thu Duc City

Year	No Dryness	Low Dryness	Average Dryness	High Dryness	Very High Dryness	ENSO
1990	25.37	28.32	17.76	8.65	19.9	-
1995	23.9	27.17	18.87	9.65	20.41	El Nino
2000	18.07	24.48	25.14	11.87	20.45	La Nina
2005	22.61	17.38	18.88	11.49	29.64	El Nino
2010	20.69	21.05	21.41	11.36	25.49	El Nino
2015	12.74	12.7	23.66	17.68	33.23	El Nino
2020	12.36	11.65	20.16	18.12	37.71	-
2023	13.81	18.2	32.49	9.54	25.96	La Nina
2024	13.23	15.83	26.21	17.13	27.61	El Nino

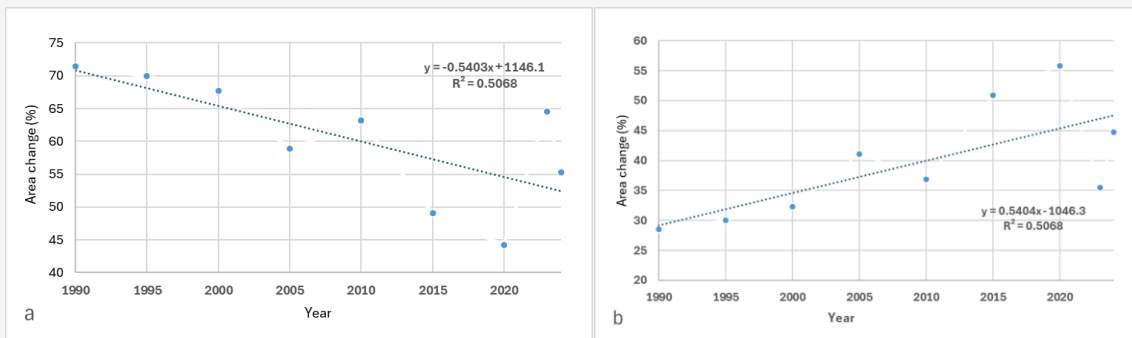


Figure 9: The trend to change the area ratio of dry-term levels from 1990-2024 in Thu Duc City: (a) low dryness (b) high dryness

For example, in the case of the Very High Dryness level, it accounted for 19.90% in 1990, increased to 29.64% in 2000, and reached 37.71% in 2020. The proportion of areas with no dryness or low dryness level is trending downward, with the No Dryness area in 1990 accounting for 25.37%, decreasing to 13.13% in 2024; the Low Dryness area in 1990 represented 28.32%, dropping to 15.83% in 2024. In the years 2015 and 2020, the drought rate remained high, with High Dryness, and Very High Dryness values of 18.12%, and 37.71%, respectively in the year 2020. At the same time, when classifying the results into

two groups of low-drought (no dryness, low dryness, moderate dryness levels) and high drought (high and extremely high dryness levels), showing two distinct trends are observed: the low-drought group is likely declining, while the high-drought group tends to increase, with the determination coefficient R^2 of 0.51. This indicates that the model explains approximately 51% of the variation in drought trends, suggesting a moderate correlation. This further reinforces the results shown in Figure 9, that drought in Thu Duc City is likely increasing both in size and quantity over the years.

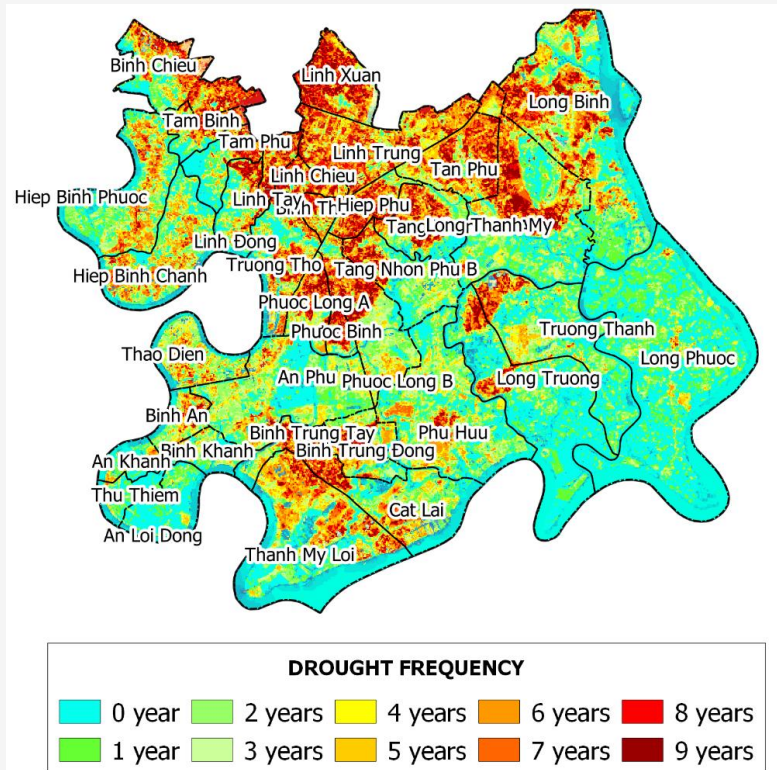


Figure 10: The frequency of drought occurrence of the observation years in Thu Duc City

Through exploring the frequency of drought occurrence at high and very high levels (Figure 10), in years of observation, it can be seen that the area with a high frequency of droughts is in Northern areas (Linh Trung, Linh Xuan, Linh Chieu, Hiep Phu, Tan Phu, Long Thanh My, Long Binh, Binh Chieu) and some wards in the South and Southwest such as Binh Trung Dong, Cat Lai, Binh An. In the East, where NDVI and NDWI indexes are always high, the frequency of drought appears very little, especially in Long Truong and Long Phuoc wards. The statistics in Table 4 clearly show that the results obtained have a certain correlation with the respective El Niño and La Nina events [23] and [24]: high and extremely high-dry drought tend to rise during the El Niño phase (1995, 2005, 2010, 2015, 2020, 2024) and decline during the La Nina phase (2000, 2023). This is also consistent with the theory related to the impact of ENSO on weather and natural disasters in Vietnam, as the results demonstrate that when El Niño conditions, the average monthly temperatures are higher than usual, with winter showing a more pronounced difference than summer, and the southern regions being more affected than the northern ones. Conversely, under La Nina conditions, the average temperatures of the months are lower than normal, with the North being more affected than the South.

El Niño often causes a shortage of rainfall in almost all regions of the country, ranging from 25-50%, leading to a high risk of localized or widespread drought [25].

2.4 Landcover Change

To ensure clearer and more reliable research results, the relationship between Drought Index and the Land Cover classification within the same time period in Thu Duc City. The land cover classification results for selected years within the period 1990–2023 are presented in Figure 11. The comparison between the drought map based on the NDDI index (Figure 7) and the Land cover maps (Figure 10) indicates that areas with high drought levels are mainly concentrated in urban regions. Specifically, areas with high NDDI values, representing severe drought conditions, coincide with regions characterized by high construction density, limited vegetation cover, and heat-absorbing surfaces, such as city centers and industrial zones. This clearly demonstrates the impact of urbanization on drought conditions, as surfaces made of concrete, asphalt, and other construction materials reduce water infiltration capacity while intensifying the urban heat island effect, leading to higher surface temperatures and accelerated water evaporation.

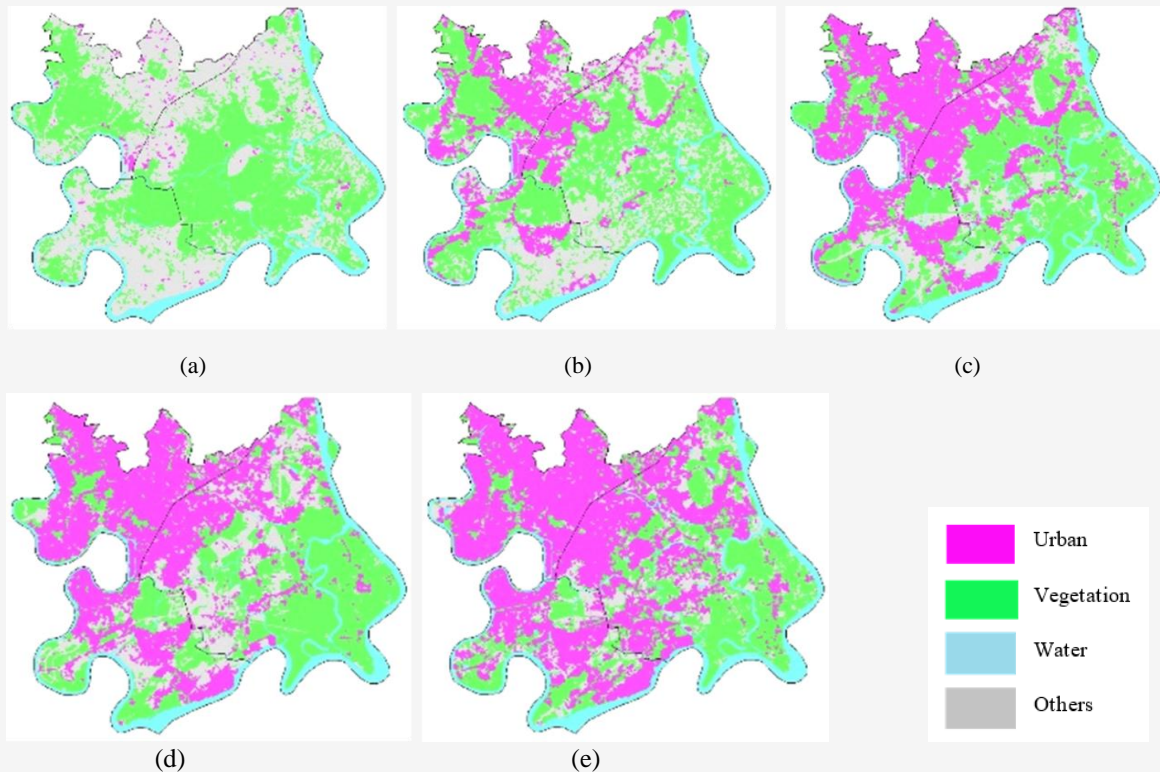


Figure 11: Land cover classification (a) 1990 (b) 2000 (c) 2008 (d) 2015 (e) 2023

The consistency between the NDDI analysis results and the distribution of land cover not only confirms the accuracy of the drought assessment method but also highlights the importance of sustainable urban planning. Expanding green spaces, preserving natural ecosystems, and implementing appropriate planning solutions can help mitigate the negative impacts of drought and climate change, contributing to a more stable and sustainable living environment in the future.

3. Conclusion

The study has successfully assessed the trends and developments of drought in Thu Duc City over the past three decades, focusing on the dry seasons of selected years. By utilizing the NDDI, derived from NDVI and NDWI, the research provided valuable insights into the spatial and temporal dynamics of drought within the study area. Significant findings included an increasing trend in drought-affected areas, particularly after 2000, and the identification of zones with varying frequencies of drought occurrence. The study also revealed a strong correlation between the ENSO phenomenon and drought severity, underlining the importance of climatic factors in shaping local drought conditions. Additionally, the land cover classification results further reinforced these findings by demonstrating

that urbanized areas, characterized by extensive impervious surfaces and limited vegetation, experienced more intense drought conditions. In contrast, regions with higher vegetation cover and water bodies exhibited lower drought severity, emphasizing the role of land use and surface characteristics in drought susceptibility. These results offer a comprehensive understanding of drought patterns, which are crucial for effective urban planning and resource management in Thu Duc City.

Despite these contributions, certain limitations should be acknowledged. Cloud cover in some Landsat images created challenges in data processing, leading to potential gaps in information. Furthermore, the lack of field data for calibration and validation reduced the overall accuracy and reliability of the assessment. These limitations highlight the need for further research to enhance the robustness of drought monitoring in the region. Future studies should consider incorporating a broader range of drought indices to capture diverse aspects of drought conditions and ensure a more comprehensive analysis. Additionally, conducting field surveys would not only improve the validation of satellite-based findings but also provide valuable ground-level insights into drought impacts.

Expanding the temporal scope by analyzing annual or seasonal variations in greater detail, as well as extending the spatial scope to include surrounding areas, would offer a more holistic view of drought dynamics. Further investigations into land cover changes over time, particularly in relation to urban expansion and vegetation loss, would provide deeper insights into the interplay between land use and drought severity. Integrating land cover dynamics into drought modeling could improve the accuracy of predictions and support more effective mitigation strategies. Moreover, exploring the socio-economic impacts of drought could provide a deeper understanding of how drought affects local communities, informing the development of adaptive strategies.

These improvements would significantly enhance the reliability and applicability of drought monitoring and mitigation efforts in Thu Duc City. As a newly established urban area, Thu Duc requires precise, actionable information to guide its development in a sustainable and climate-resilient manner. By addressing the outlined limitations and recommendations, future research can build upon this study to deliver more robust, multidimensional assessments of drought and its impacts.

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References

- [1] AghaKouchak, A., (2015). A Multivariate Approach for Persistence-based Drought Prediction: Application to the 2010–2011 East Africa Drought. *Journal of Hydrology*, Vol. 526, 127–135. <https://doi.org/10.1016/j.jhydrol.2014.09.063>.
- [2] Dai, A., (2011). Drought under Global Warming: A Review. *Wiley Interdisciplinary Reviews: Climate Change*, Vol. 2, 45–65.
- [3] Hobbins, M. T., Wood, A., McEvoy, D. J., Huntington, J. L., Morton, C., Anderson, M. and Hain, C., (2016). The Evaporative Demand Drought Index. Part I: Linking Drought Evolution to Variations in Evaporative Demand. *Journal of Hydrometeorology*, Vol. 17, 1745–1761, <https://doi.org/10.1175/JHM-D-15-0121.1>.
- [4] Wilhite, D. A. and Glantz, M. H., (1985). Understanding the Drought Phenomenon: The Role of Definitions. *Water International*, Vol. 10(3), 111-120.
- [5] Mishra, A. K. and Singh, V. P., (2010). A Review of Drought Concepts. *Journal of Hydrology*, Vol. 391(1-2), 202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>.
- [6] AghaKouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D. and Hain C. R., (2015). Remote Sensing of Drought: Progress, Challenges and Opportunities. *Reviews of Geophysics*, Vol. 53, 452–480. <https://doi.org/10.1002/2014RG000456>.
- [7] Campbell, J. B. and Wynne, R. H., (2011). *Introduction to Remote Sensing*; Guilford Press: New York, NY, USA. <https://doi.org/10.3390/rs5010282>.
- [8] Duc, T., Thao, N., Long, T., Van Tan, P., Thi Thu Huong, C. and Van Hiep, N., (2022). Investigation of Drought Characteristics Across Vietnam During Period 1980-2018 Using SPI and SPEI Drought Indices. *VNU Journal of Science: Earth and Environmental Sciences*, Vol. 38(1). <https://doi.org/10.25073/2588-1094/vnuees.4757>.
- [9] Hung, T. L. and Hoai, K. D., (2015). Remote Sensing Application for Drought Assessment in Bac Binh District, Binh Thuan Province. *Journal of Ho Chi Minh City University of Education*, Vol. 5(70), 128-139.
- [10] Suwanlee, S., Keawsomsee, S., Sangjan, W., Som-ard, J., Siripattanachotikul, K., Ninsawat, S., and Nudthawud, H. (2024). Spatio-Temporal Drought Monitoring in the Chi River Basin from 2001–2020 Using MODIS Time Series Data and Google Earth Engine. *International Journal of Geoinformatics*, Vol. 1(1), 43–55. <https://doi.org/10.52939/ijg.v2i1i.3789>.
- [11] Samanta, S. (2024). Identification of Agricultural Drought through Vegetation Health Analysis at Erap Station under the Markham Valley of Papua New Guinea. *International Journal of Geoinformatics*, Vol. 20(11), 106–115. <https://doi.org/10.52939/ijg.v20i11.3691>.

- [12] Preedapirom, P., Robert, O., Onchang, R., and Jeefoo, P. (2024). Drought Monitoring Using MODIS Satellite-Based Data in Kamphaeng Phet Province, Thailand. *International Journal of Geoinformatics*, Vol. 20(1), 1–11. <https://doi.org/10.52939/ijg.v20i1.3019>.
- [13] Thavorntam, W., and Shah Nawaz. (2022). Evaluation of Drought in the North of Thailand using Meteorological and Satellite-Based Drought Indices. *International Journal of Geoinformatics*, Vol. 18(5), 13–26. <https://doi.org/10.52939/ijg.v18i5.2367>.
- [14] Phan-Hien, V., Dinh-Tung, V. and Su, Z., (2018). Monitoring Drought via TVDI Derived from 2000-2015 MODIS Data: A Case Study of the Vietnamese Mekong River Delta. *The 39th Asian Conference on Remote Sensing*, Kuala Lumpur, Malaysia.
- [15] People's Committee of Thu Duc City, (2022). *The General Planning Tasks Regarding Thu Duc city in Ho Chi Minh City until 2040*. Vietnam. <https://en.vietnamplus.vn/general-planning-tasks-for-thu-duc-city-approved-post208171.vnp>.
- [16] Ngoc, D. B., Oanh, N. T., Hien, P. Q., Ngoc, T. T. and Xuyen, L. N., (2023). Research on the Google Earth Engine Platform to Build a System to Identify Landslide Locations from Multi-temporal Remote Sensing Data. *The Journal of Geodesy and Cartography*, Vol. 57, 9-15.
- [17] Amundson, (2020). Landsat Thematic Mapper (TM) Collection 2 (C2) Level 1 (L1) Data Format Control Book. *Department of the Interior U.S. Geological Survey*.
- [18] Landsat 8 The Landsat Data Continuity Mission. *United States Geological Survey*. [Online]. Available: <https://www.usgs.gov/landsat-missions/landsat-8>. [Accessed Sep. 18, 2024].
- [19] Hoang, N. V., Ngan, H. T. K. and Vuong, N. D., (2020). Research on the Application of Google Earth Engine Platform to Create a Drought Monitoring Map for the Dong Nai River Basin in the Southeast region. *Journal Science and Technology Water Resources*, Vol. 58, 47-53.
- [20] Thammaboribal, P. (2024). Investigating Land Surface Temperature Variation and Land Use Land Cover Changes in Pathumthani, Thailand (1997-2023) using Landsat Satellite Imagery: A Comprehensive Analysis of LST and Urban Hot Spots (UHS). *International Journal of Geoinformatics*, Vol. 20(2), 27–41. <https://doi.org/10.52939/ijg.v20i2.3063>.
- [21] Gao, B. C., (1996). NDWI - A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sensing of Environment*, Vol. 58(3), 257-266.
- [22] Tucker, C. J., (1979). Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sensing of Environment*, Vol. 8(2), 127-150.
- [23] McFeeters, S. K., (2013). Using the Normalized Difference Water Index (NDWI) within a Geographic Information System to Detect Swimming Pools for Mosquito Abatement: A Practical Approach. *Remote Sensing*, Vol. 5(7), 3544-3561.
- [24] El Niño and La Niña Years and Intensities. *Golden Gate Weather Services*. [Online]. Available: <https://ggweather.com/enso/oni.htm> [Accessed Sep. 20, 2024].
- [25] Thuc, T., Thuan, N. T. H. and Khiem, M. V., (2023). El Niño, La Nina and their Impact on Weather and Climate of Vietnam. *Vietnam Journal of Sciences and Technology*, Vol. 7, 53-56.