



Applicability of Remote Sensing Techniques in Drought Predicting: A Case Study in Ben Tre Province, Vietnam

X.D. Tran^{1,2}, T. L. Phan^{1,2}

10.18805/ag.DF-642

ABSTRACT

Background: Drought poses significant threats to ecosystems, agriculture and the environment, including reduced crop yields, habitat degradation and increased risk of forest fires and soil erosion. In addressing this issue, remote sensing technology (RST) has emerged as a valuable tool for studying and monitoring drought phenomena, offering advantages over traditional research methods. **Methods:** This study focuses on the application of RST, specifically utilizing Landsat satellite images, to calculate drought indices and develop drought maps for the Ben Tre province in Vietnam. The research involved the analysis of Landsat satellite images collected between 2000 and 2020, using various drought indices such as TCI, VCI, SAVI and WSVI.

Result: By employing these indices, the study was able to classify the levels of drought and generate a drought map for the study area. The findings revealed that the coastal regions encompassing Thanh Phu, Ba Tri and Binh Dai districts face a high risk of drought during the dry season.

Key word: Ben tre, Drought index, Drought, Remote sensing, Satellite image.

INTRODUCTION

Drought is a highly complex phenomenon caused by natural and human factors such as variations in atmospheric circulation patterns or high-pressure systems, climate change, deforestation activities, environmental pollution and unsustainable land and water management. In recent years, drought in the Mekong Delta (Vietnam) has tended to increase. Ben Tre is a province significantly affected by climate change, with trends of increasing average temperatures, decreasing rainfall and deep seawater intrusion affecting crop productivity and causing substantial harm to the province's socio-economy. Therefore, researching, evaluating and determining the possibility of drought has practical significance for devising disaster prevention solutions and achieving sustainable socio-economic development.

Comprehensive assessments of the current status, causes, development and trends of different types of droughts are based on drought indices and thresholds such as the Penman-Monteith Dryness Index, the Standardized Precipitation Index (SPI), the Sazonov Index, the Surface Water Supply Index (SWSI), the Reclamation Drought Index (RDI) (Dinh and Dang, 2022). Nowadays, the development of remote sensing and GIS technology is being widely applied in drought monitoring and forecasting (Rajalakshimi *et al.*, 2023; Phung, 2024). Drought indices calculated from satellite-derived surface parameters are an effective method for creating drought maps, visually indicating drought areas, severity and frequency. From these results, researchers and local authorities can assess drought conditions and develop water resource management, agricultural production and drought prevention plans. A diverse range of satellite imagery data is utilized, from optical satellite images to radar images

¹University of Science, HCM City, Viet Nam.

²VNU-HCM, HCM City, Viet Nam, 227 Nguyen Van Cu Str., 5 District, Ho Chi Minh City, Vietnam.

Corresponding Author: X.D. Tran, University of Science, HCM City, Viet Nam. Email: txdung@hcmus.edu.vn

How to cite this article: Tran, X.D. and Phan, T.L. (2024). Applicability of Remote Sensing Techniques in Drought Predicting: A Case Study in Ben Tre Province, Vietnam. *Agricultural Science Digest*. doi: 10.18805/ag.DF-642.

Submitted: 08-07-2024 **Accepted:** 26-08-2024 **Online:** 10-09-2024

such as Landsat (Sun *et al.*, 2020), Sentinel (Urban *et al.*, 2018), or MODIS (Gümüř *et al.*, 2023). Researchers can assess the drought status of areas of interest using indices extracted from satellite images, such as the Normalized Difference Vegetation Index (NDVI), the Temperature Condition Index (TCI), the Vegetation Condition Index (VCI), the Water Supplying Vegetation Index (WSVI) combined with other indices like SPI (Okal *et al.*, 2019), or the Standardized Precipitation Evaporation Index (SPEI) (Páscoa *et al.*, 2020). Additionally, integrating multiple indices provides a comprehensive assessment of the causes and progression of drought, as Sun *et al.* (2020) used the Vegetation Drought Monitor Synthesized Index (VDSI) by integrating the Standardized Vegetation Index (SVI), the Standardized Water Index (SWI) and the Evaporative Stress Index (ESI), Zhang *et al.* (2021) integrated precipitation, water balance, soil temperature and crop development to develop the Comprehensive Drought Monitoring Index (CDMI). In Vietnam, there have also been numerous researchers applying remote sensing to create drought maps and assess drought risk in areas such as Binh Thuan (Trinh and Dao, 2015), Nghe An (Do *et al.*,

2017), Ha Tinh (Bui *et al.*, 2019), Ninh Thuan (Do *et al.* 2020, Dang *et al.*, 2022). Research results indicate that drought indices are closely related and can be effectively applied in creating drought risk maps, contributing to responding to and minimizing the impact of drought on the living environment and people's production activities.

MATERIALS AND METHODS

Ben Tre is a province in the Mekong Delta, with a natural area of 2,379 km², formed by the alluvium from four branches of the Mekong River (Fig 1). The terrain of Ben Tre is relatively flat, with a dense network of canals. The province is in a region influenced by a tropical monsoon climate, the Northeast Monsoon (December - April) and the Southwest Monsoon (May - November). The average annual temperature ranges from 26°C to 27°C. The annual rainfall ranges from 1,210 mm to 1,500 mm. During the dry season, rainfall accounts for approximately 2% to 6% of the total annual rainfall (Fig 2). In recent years, Ben Tre has experienced a decrease in rainfall and an increase in temperature, leading to drought conditions in the province.

The combination of low rainfall and reduced upstream flow from the Mekong River has led to earlier and more

extensive saltwater intrusion inland, affecting the water supply for agricultural production and daily life (Ben Tre Statistical Office, 2023).

Data and method

The data used in this study consists of Landsat satellite images from the U.S. Geological Survey (<https://glovis.usgs.gov/app>), collected from 2000 to 2020 (Table1). The study analyzed and calculated the drought indices using these satellite image data. After obtaining data from the drought index calculations, the data were processed to classify the drought levels and create a drought map for each drought index (Fig 3).

Calculating parameters

Converting digital number (DN) value to spectral radiance (L_p), spectral reflectance (ρ_p) value

Sensors record the intensity of electromagnetic radiation from the Earth's surface as digital number (DN) values; therefore, the first step is to convert the digital number values into the actual electromagnetic radiation values.

- For Landsat 5 and Landsat 7 images (Chander and Markham, 2003):

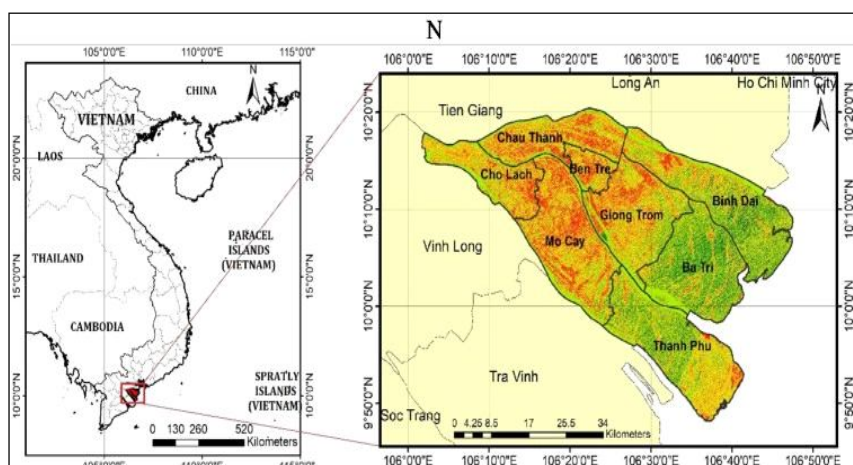


Fig 1: Study area.

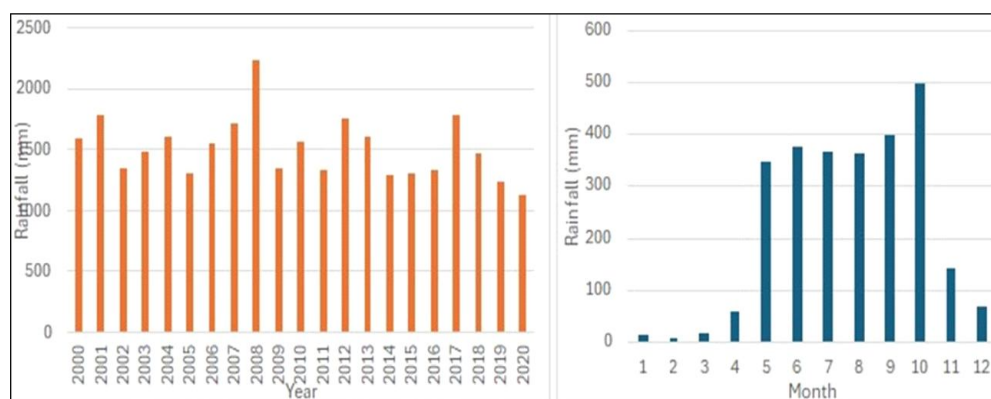


Fig 2: The annual rainfall and its monthly average in the period 2000-2020.

$$L_{\lambda} = \left(\frac{L_{\max\lambda} - L_{\min\lambda}}{Q_{\text{cal max}} - Q_{\text{cal min}}} \right) (Q_{\text{cal max}} - Q_{\text{cal min}}) + L_{\min\lambda} \quad (1)$$

L_{λ} : Spectral radiance.

Q_{cal} : Quantized calibrated pixel value.

$Q_{\text{cal max}}$: Maximum quantized calibrated pixel value.

$Q_{\text{cal min}}$: Minimum quantized calibrated pixel value.

$L_{\max\lambda}$: Spectral radiance that is scaled to $Q_{\text{cal max}}$.

$L_{\min\lambda}$: Spectral radiance that is scaled to $Q_{\text{cal min}}$.

After that, the spectral radiance values are converted to spectral reflectance values:

$$\rho_p = \frac{\pi L_{\lambda} d^2}{\text{ESUN}_{\lambda} \cos \theta_s} \quad (2)$$

ρ_p : Planetary reflectance.

d : Earth–sun distance.

ESUN_{λ} : Mean solar exoatmospheric irradiances.

θ_s : Solar zenith angle.

- For Landsat 8 images (U.S. Geological Survey, 2019):

$$L_{\lambda} = M_L Q_{\text{CAL}} + A_L \quad (3)$$

M_L : Radiance multiplicative scaling factor.

A_L : Radiance additive scaling factor.

Spectral radiance values are converted to spectral reflectance values:

$$\rho_{\lambda}' = M_p Q_{\text{CAL}} + A_p \quad (4)$$

ρ_{λ}' : Planetary Spectral Reflectance, without correction for solar angle.

M_p : Reflectance multiplicative scaling factor for the band.

A_p : Reflectance additive scaling factor for the band.

The formula for correcting the sun angle for the spectral reflectance values:

$$\rho_{\lambda} = \frac{\rho_{\lambda}'}{\cos(\theta_{sz})} = \frac{\rho_{\lambda}'}{\cos(\theta_{se})} \quad (5)$$

θ_{se} : Local sun elevation angle.

θ_{sz} : Local solar zenith angle.

➤ Normalized difference vegetation index

NDVI is the ratio of the difference in surface spectral reflectance values between the near-infrared (NIR) and the red (RED) band to their sum, used to indicate the vegetation concentration on the ground:

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (6)$$

NIR: Surface spectral reflectance value in the near-infrared band.

RED: Surface spectral reflectance value in the red band.

The vegetation proportion (P_v)

P_v is the vegetation fraction in a pixel. P_v is calculated based on the correlation with the thresholds and (Sobrino *et al.*, 2004):

$$P_v = \left[\frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \right]^2 \quad (7)$$

Surface emissivity (ϵ)

Surface emissivity is estimated from the NDVI threshold values, considering three different cases (Sekertekin and Bonafoni, 2020):

Table 1: List of collected Landsat satellite images.

Satellite	Date	Resolution
Landsat 5 (MT)	03/03/2000	30 m
Landsat 7 (ETM+)	02/13/2002	30 m
Landsat 5 (MT)	02/13/2005	30 m
Landsat 5 (MT)	02/03/2007	30 m
Landsat 5 (MT)	02/08/2009	30 m
Landsat 8 (OLI/TIRS)	02/06/2014	30 m
Landsat 8 (OLI/TIRS)	02/09/2015	30 m
Landsat 8 (OLI/TIRS)	02/28/2016	30 m
Landsat 8 (OLI/TIRS)	02/14/2017	30 m
Landsat 8 (OLI/TIRS)	02/23/2020	30 m

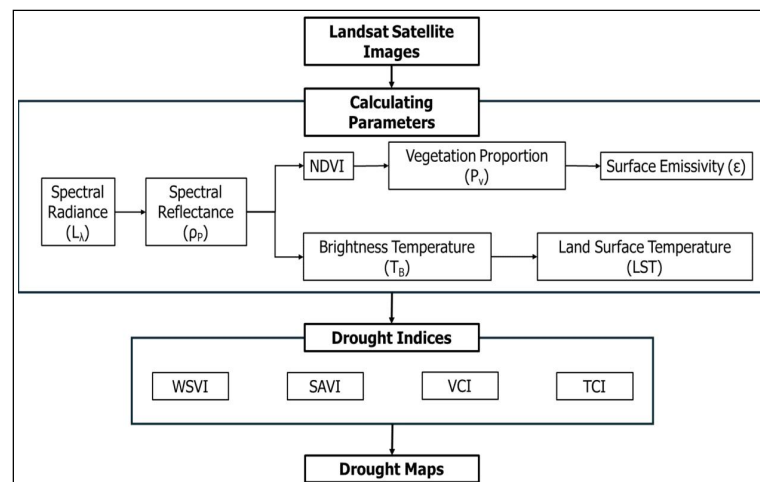


Fig 3: The satellite image processing procedure.

- Landsat 5 and Landsat 7 (band 6):

$$\varepsilon = \begin{cases} 0.979-0.035\rho_R & \text{NDVI} < 0.2 \\ 0.004P_V+0.986 & 0.2 \leq \text{NDVI} \leq 0.5 \\ 0.99 & \text{NDVI} > 0.5 \end{cases} \quad (8)$$

- Landsat 8 (band 10):

$$\varepsilon = \begin{cases} 0.979-0.046\rho_R & \text{NDVI} < 0.2 \\ 0.987P_V+0.971(1-P_V)+d\varepsilon & 0.2 \leq \text{NDVI} \leq 0.5 \\ 0.987+d\varepsilon & \text{NDVI} > 0.5 \end{cases} \quad (9)$$

ρ_R : Reflectance value of the red band.

ε_V , ε_S : Vegetation and soil emissivity.

$d\varepsilon$: Cavity effect due to surface roughness ($d\varepsilon = 0$ for flat surfaces).

Brightness temperature (T_B)

The spectral radiance values calculated in the previous step are used to compute the corresponding brightness temperature T_B (U.S. Geological Survey, 2019):

$$T_B = \frac{K_2}{\ln \left(1 + \frac{K_1}{L_\lambda} \right)} \quad (10)$$

T_B : Brightness temperature.

K_1 , K_2 : Band-specific thermal conversion constant from the metadata.

Land surface temperature (LST)

Surface temperature is calculated based on the brightness temperature, taking into account the effect of emissivity. Surface temperature, which used to assess the overall health of vegetation, soil moisture conditions and the impact of temperature, is determined by the formula (Wukelic *et al.*, 1989):

$$\text{LST} = \frac{T_B}{1 + \left(\frac{\lambda T_B}{\rho} \right) \ln \varepsilon} \quad (11)$$

λ : Central band wavelength of emitted radiance.

$\rho = \frac{hc}{\sigma}$, σ Boltzmann constant (1.38×10^{-23} J.K⁻¹).

h : Planck's constant (6.626×10^{-34} J.s).

c : Light velocity (2.998×10^8 m/s).

Drought indices

Temperature condition index

The TCI is used to identify drought situations related to temperature, computed by the formula (Kogan, 1995):

$$\text{TCI} = 100 \frac{\text{LST}_{\max} - \text{LST}}{\text{LST}_{\max} - \text{LST}_{\min}} \quad (12)$$

$\text{LST}_{\max}$: Maximum surface temperature value.

$\text{LST}_{\min}$: Minimum surface temperature value.

Vegetation condition index

The VCI is considered a measure to evaluate the growth and development status of the vegetation cover, determined by the formula (Kogan, 1995):

$$\text{VCI} = 100 \frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \quad (13)$$

NDVI: Vegetation index value at the pixel.

$\text{NDVI}_{\max}$: Maximum vegetation index value.

$\text{NDVI}_{\min}$: Minimum vegetation index value.

Soil adjusted vegetation index

The SAVI is calculated by combining the NDVI calculation with an additional parameter L to increase accuracy for areas with low vegetation (Huete, 1988):

$$\text{SAVI} = 100 \frac{\text{NIR} - \text{RED}}{\text{NIR} - \text{RED} + L} (L+1) \quad (14)$$

NIR: Surface spectral reflectance value in the near-infrared channel.

RED: Surface spectral reflectance value in the red channel.

L: Soil brightness adjustment factor.

Water supplying vegetation index

The WSVI is a combination of the NDVI and the LST to determine soil moisture. The formula for calculating the WSVI is as follows (Elhag and Bahrawi, 2017):

$$\text{WSVI} = \frac{\text{NDVI}}{\text{LST}} \quad (15)$$

RESULTS AND DISCUSSION

After processing the satellite imagery data, the study obtained the calculation results for the degree and distribution of drought in the Ben Tre province. During the image processing and the creation of drought maps, each index is calculated using different parameters, which reflect various aspects of drought assessment. In the used dataset, the quality of satellite images is influenced by several factors, such as cloud cover, which affects the calculation results. Therefore, the assessment of drought from 2000 to 2020 for each index yields a different number of results. The drought maps presented in the study are the clearest representations of the drought status in the study area (Table 2).

In general, the classification results for drought according to different indices will yield varying values. The SAVI, VCI and WSVI indices are related to vegetation contrast and the impact of environmental factors such as climate, soil and water, providing information about the state of vegetation growth, especially in arid and drought conditions.

According to the calculation results for WSVI, SAVI and VCI, the areas with the thinnest vegetation and poorest vegetation growth are located in coastal regions. Areas

with high vegetation cover, where VCI values range from 60% to 100%, are found in the northwestern parts of the province, including Chau Thanh, Cho Lach, Mo Cay Bac, Mo Cay Nam, Giong Trom and Ben Tre City.

Temperature condition index (TCI)

The TCI assumes that during drought periods, soil moisture decreases significantly, affecting plants and trees. TCI value <50% corresponds to vegetation degradation due to drought or severe weather conditions caused by high temperatures. In Ben Tre, most districts have high TCI values ranging from 50% to 100% indicating low temperature differences, TCI values around 30% to 50%

are very few and scattered (Fig.4). Thus, the calculation results indicate that Ben Tre has a mild drought level. The average drought area over the years is approximately 34,779.7 hectares (14.7% of the province's area).

Vegetation condition index (VCI)

The VCI value indicates the extent to which vegetation is growing or declining in response to weather conditions. VCI values ranging from 50 to 100% indicate healthy vegetation and that the area is neither drought-stricken nor excessively wet. Values from 35% to 50% suggest moderate drought and values from 20% to 35% indicate severe drought levels. The drought analysis according to

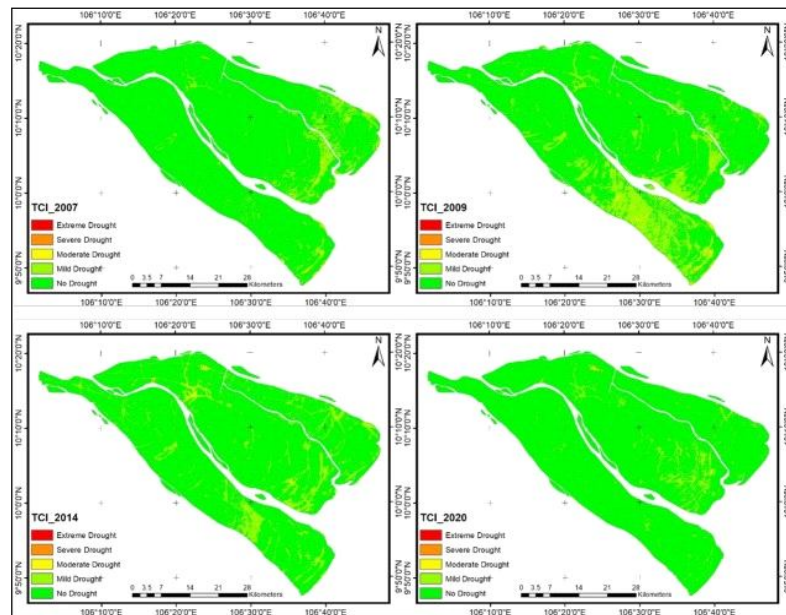


Fig 4: Drought map according to TCI.

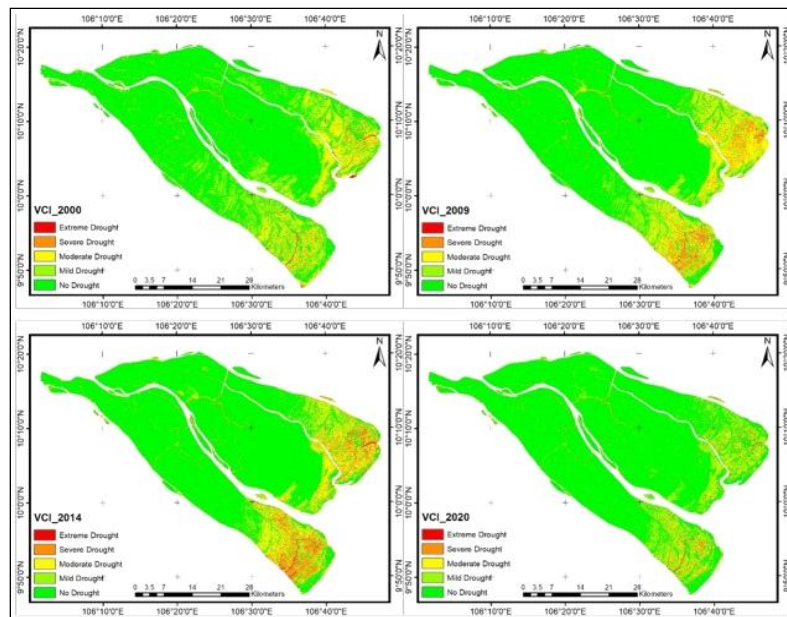


Fig 5: Drought map according to VCI.

the VCI index shows that Ben Tre is affected by moderate drought conditions (Fig 5). This situation is mainly concentrated in the coastal areas, including the districts of Thanh Phu, Ba Tri and Binh Dai, with low VCI values ranging from 35% to 50%. High VCI values around 60% to 100% are distributed in the northwestern part of the province, including Chau Thanh, Cho Lach, Mo Cay Bac, Mo Cay Nam, Giong Trom and Ben Tre City, indicating the best vegetation cover growth in this area. In the years 2006, 2008, 2009 and 2014, severe drought levels are more evident, with VCI values ranging from 20% to 35% and VCI

values below 20% accounting for a higher proportion. Overall, the drought area fluctuates approximately from 40,000 hectares to 60,000 hectares (17.1% - 25.6% of the province's area).

Soil adjusted vegetation index (SAVI)

SAVI can be used to estimate the photosynthetic activity of vegetation and monitor drought. Drought due to low rainfall or increased temperature reduces SAVI in vegetated areas, so the SAVI provides very useful information for drought monitoring. According to the drought distribution map

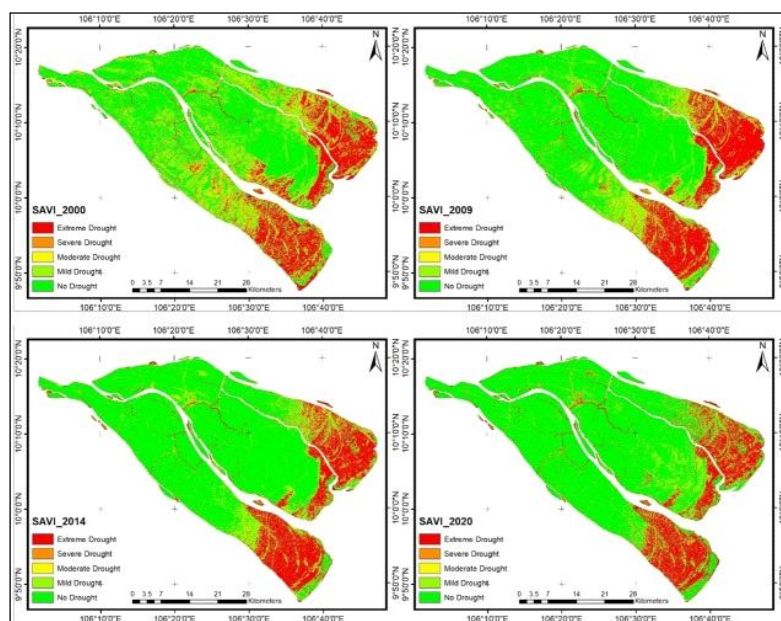


Fig 6: Drought map according to SAVI.

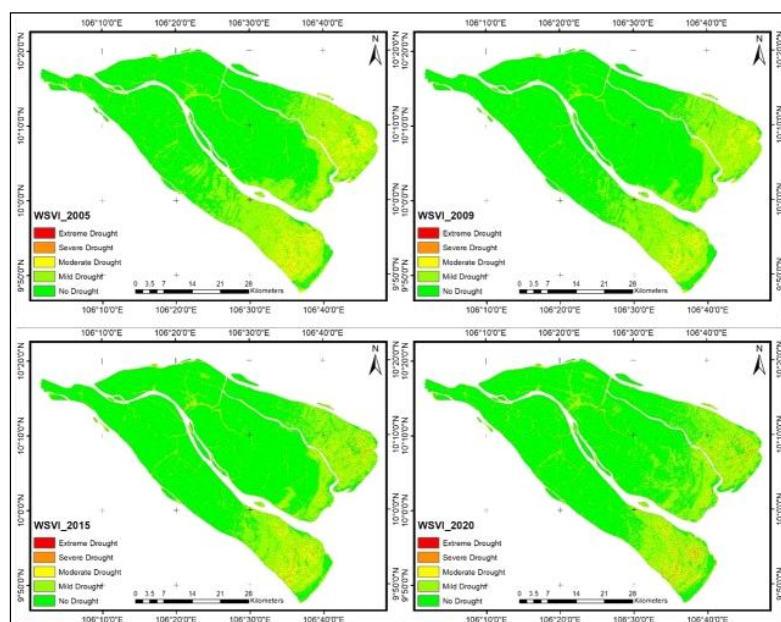


Fig 7: Drought map according to WSVI.

Table 2: Classification of drought levels for different indices.

Level	SAVI	WSVI	VCI	TCI
Extreme Drought	<0.1	<-0.02	<20	<10
Severe Drought	0.1-0.13	-0.02-0.01	20-35	10-20
Moderate Drought	0.13-0.15	-0.01-0	35-50	20-30
Mild Drought	0.15-0.28	0-0.015	50-60	30-50
No Drought	>0.28	>0.015	60-100	50-100

based on the SAVI, it can be seen that severe drought conditions are primarily concentrated in the coastal districts of Thanh Phu, Binh Dai and Ba Tri (Fig 6). This area is frequently affected by drought conditions, as reflected by the thin and poorly developing vegetation. The drought area varies unevenly across the years, ranging from 60,000 hectares to 120,000 hectares (25.6% - 51.3% of the province's area), with an average value of 93,889.3 hectares.

Water supplying vegetation index (WSVI)

The lower WSVI values indicate less water supply to vegetation and more severe droughts, whereas higher values indicate less severe droughts. The area with low WSVI values (-0.01 - 0), is mostly concentrated in Thanh Phu, Ba Tri and Binh Dai, indicating that this area has relatively lower moisture compared to the green areas (Fig.7). Most of the drought area each year fluctuates around 60,000 hectares (25.6% area).

CONCLUSION

The study utilized remote sensing and GIS to create a drought map for the Ben Tre province using Landsat satellite imagery. The calculated results for drought distribution across different indices indicate that Ben Tre province is experiencing varying degrees of drought primarily concentrated in the coastal areas of the Thanh Phu, Ba Tri and Binh Dai districts reflected by the indices, moderate drought levels according to the VCI and WSVI and severe drought levels according to the SAVI.

The drought severity calculated in the study largely depends on surface temperature and vegetation indices, resulting in different values of drought areas according to the various indices. Combining remote sensing technology and GIS is an effective and objective method for assessing drought. Through GIS data analysis, it is possible to determine the drought area and the degree of variation in each region. The results are useful for identifying areas at risk of drought at the local level.

ACKNOWLEDGEMENT

This research is funded by University of Science, VNU-HCM under grant number T2022-09.

Conflict of interest

The authors declare that there are no conflicts of interest.

REFERENCES

- Ben Tre Statistical Office (2023). Statistical Yearbook of Ben Tre 2022. Ho Chi Minh City General Publisher.
- Bui, T.K.T., Nguyen, Q.P., Nguyen, M.C. (2019). Application of GIS and remote sensing images in drought monitoring and warnings. Proceedings of the Annual Scientific Conference-Thuy loi University. 326-328.
- Chander, G. and Markham, B. (2003). Revised landsat 5 TM radiometric calibration procedures and Post-calibration dynamic ranges. IEEE Transactions on Geoscience and Remote sensing. 41: 2674- 2677.
- Dang, Q.K., Duong, V.K., Duong, H.Y. (2022). Research and application of remote sensing and GIS technology to build agricultural drought maps in Ninh Thuan province. Vietnam Journal of Hydro- Meteorology. 736: 12-24.
- Department of the Interior U.S. Geological Survey (2019). Landsat 8 (L8) Data Users Handbook. USA.
- Dinh, K.H.T. and Dang, T.A. (2022). Assessment of brackish water usability for irrigating the coastal sugarcane fields under the background of saline intrusion. Indian Journal of Agricultural Research. doi: 10.18805/IJARE.AF-710.
- Do, T.N.A., Nguyen, Q.P., Nguyen, H.S. (2017). Research methods agricultural drought warning in downstream of Ca River. Journal of Water Resources and Environmental Engineering. 56: 24-33.
- Do, T.P.T., Duong, T.M.C., Le, A. T., Tran, T.T.V., Nguyen, T.T.H. (2020). Extracting and overlapping geospatial informations from remote sensing to mapping genegal drought of Ninh Thuan province. Journal of Mining and Earth Sciences. 61: 4 (2020), 11-24.
- Elhag, M. and Bahrawi, J. A. (2017). Soil salinity mapping and hydrological drought indices assessment in arid environments based on remote sensing techniques. Geosci. Instrum. Method. Data Syst. 6: 149-158.
- Gümüş, K.A., Balçık, F.B., Esetili, T., Kahya, C. (2023). Monitoring drought dynamics using remote sensing-based combined drought index in Ergene Basin, Türkiye. Open Geosciences. 15: 20220594.
- Huete, A.R. (1988). A Soil-Adjusted Vegetation Index (SAVI). Remote Sensing of Environment. 25: 295-309.
- Kogan, F. N. (1995). Application of Vegetation Index and Brightness Temperature for Drought Detection. Adv. Space Res. 15, 11, (11)91-(11)100.
- Okal, H.A., Ngetich, F.K., Okeyo, J.M. (2019). Spatial evaluation of droughts using selected satellite-based indices in the upper tana river watershed, kenya. International Journal of Plant and Soil Science. 30(1): 1-13.

- Páscoa, P., Gouveia, C.M., Russo, A.C., Bojariu, R., Vicente-Serrano, S. M., Trigo, R.M. (2020). Drought Impacts on Vegetation in Southeastern Europe. *Remote Sens.* 12: 2156.
- Phung, T.D. (2024). Impact of Urbanization Processes on Vegetation Cover in the Cities Over the Last Two Decades. *Agricultural Science Digest.* 44(3): 1-6.
- Rajalakshimi, P., Mahendran, P.P., Mary, P.C.N., Ramachandran, J., Kannan, P., Chelvi, R.S.S. (2023). Spatial analysis of soil Texture using GIS based geostatistics models and influence of soil texture on soil hydraulic conductivity in melur block of Madurai District, Tamil Nadu. *Agricultural Science Digest.* doi: 10.18805/ag.D-5691.
- Sekertekin, A. and Bonafoni, S. (2020). Land Surface Temperature Retrieval from Landsat 5, 7 and 8 over Rural Areas: Assessment of different retrieval algorithms and emissivity models and toolbox implementation. *Remote Sensing.* 12(2): 294.
- Sobrinho, J.A., Jiménez-Muñoz, J.C., Paolini, L. (2004). Land surface temperature retrieval from Landsat TM 5. *Remote Sens. Environ.* 90: 434-440.
- Sun, X., Wang, M., Li, G., Wang, Y. (2020). Regional-scale drought monitor using synthesized index based on remote sensing in northeast China. *Open Geosciences.* 12: 163-173.
- Trinh, L.H. and Dao, K.H. (2015). Drought risk evaluation using remote sensing: A case study in Bac Binh district, Binh Thuan province. *Journal of Science Ho Chi Minh city University of Education.* 5(70).
- Urban, M., Berger, C., Mudau, T.E., Heckel, K., Truckenbrodt, J., Odipo, V.O., Smit, I.P.J., Schmullius, C. (2018). Surface moisture and vegetation cover analysis for drought monitoring in the southern kruger national park using Sentinel-1, Sentinel-2 and Landsat-8. *Remote Sens.* 10: 1482.
- Wukelic, G.E., Gibbons, D.E., Martucci, L.M., Foote, H.P. (1989). Radiometric calibration of landsat thematic mapper thermal band. *Remote Sens. Environ.* 28: 339-347.
- Zhang, Z., Xu, W., Shi, Z., Qin, Q. (2021). Establishment of a comprehensive drought monitoring index based on multisource remote sensing data and agricultural drought monitoring. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.* 14: 2113-2126.