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Modelling of Agricultural Drought Using an Open-Source Satellite Data

Dr. Sailesh Samanta

School of Surveying and Land Studies

The PNG University of Technology

Email: sailesh.samanta@pnguot.ac.pg

About the Presenter - Dr. Sailesh Samanta

Dr. Sailesh Samanta (Associate Professor) works at the School of Surveying and Land Studies at the Papua New Guinea University of Technology. His current projects are Hydrological Modeling and Green Energy Exploration in PNG" and Better Soil and Land Information for Improving PNG's Agricultural Production.

Disciplines: Remote Sensing, Geographic Information System & Geomatics

Skills and expertise: Land Use Land cover mapping and change analysis; Climate Modeling; Environmental impact assessment; Geographic information system and remote sensing applications on Hydrology, Hazard assessment, Watershed Management, Coastal Processes, Green Energy etc.

Experiences: 16+ Years in the Remote Sensing and GIS field

Introduction: Agriculture growth

- The agricultural sector highly depends on weather, climate, and soil conditions.
- The agricultural growth may be disturbed by drought resulting in the productivity of the crops due to unfavorable soil moisture conditions.
- Soil moisture is an important variable in crop production, and agricultural drought monitoring *(Krueger et al., 2019)*.
- The fluctuation of moisture levels in the topsoil or underlying soil is attributed to minimal or absent precipitation over a specific timeframe *(Yuan et al., 2023)*.

Introduction: Water stress and crop yield

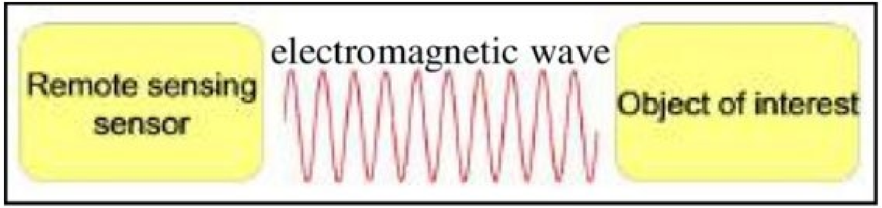
- Water stress adversely affects crop yield due to unfavorable soil moisture conditions caused by erratic rainfall and rising surface temperatures in non-irrigated regions *(Chiang et al., 2021)*.
- The Asia-Pacific region expats an average annual loss of US$404 billion due to drought, corresponding to around 1.4% of the gross domestic product of this region *(Wu et al., 2020).*
- A systematic crop monitoring system is necessary to observe and analyze the crops suffering from their growth and yield.

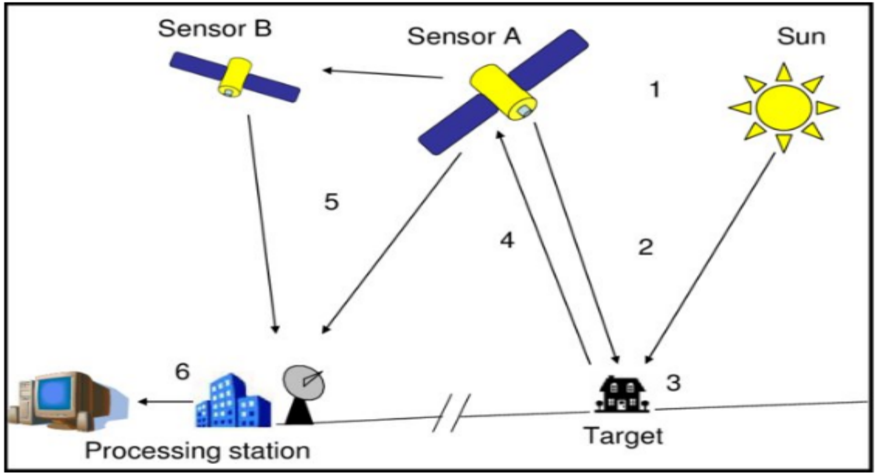
Introduction: Drought conditions monitoring

- Several conventional models were used to estimate meteorological drought based on in-situ data *(Hayes et al., 2012).*
- Factors such as heat stress on vegetation growth, land use land cover, or vegetation characteristics were not considered in these models.
- It is also difficult to observe crop health conditions on foot in larger plantation areas.
- In the last few decades, satellite remote sensing has transformed the field by reducing the dependence on conventional site-based measurements *(West et al., 2019).*

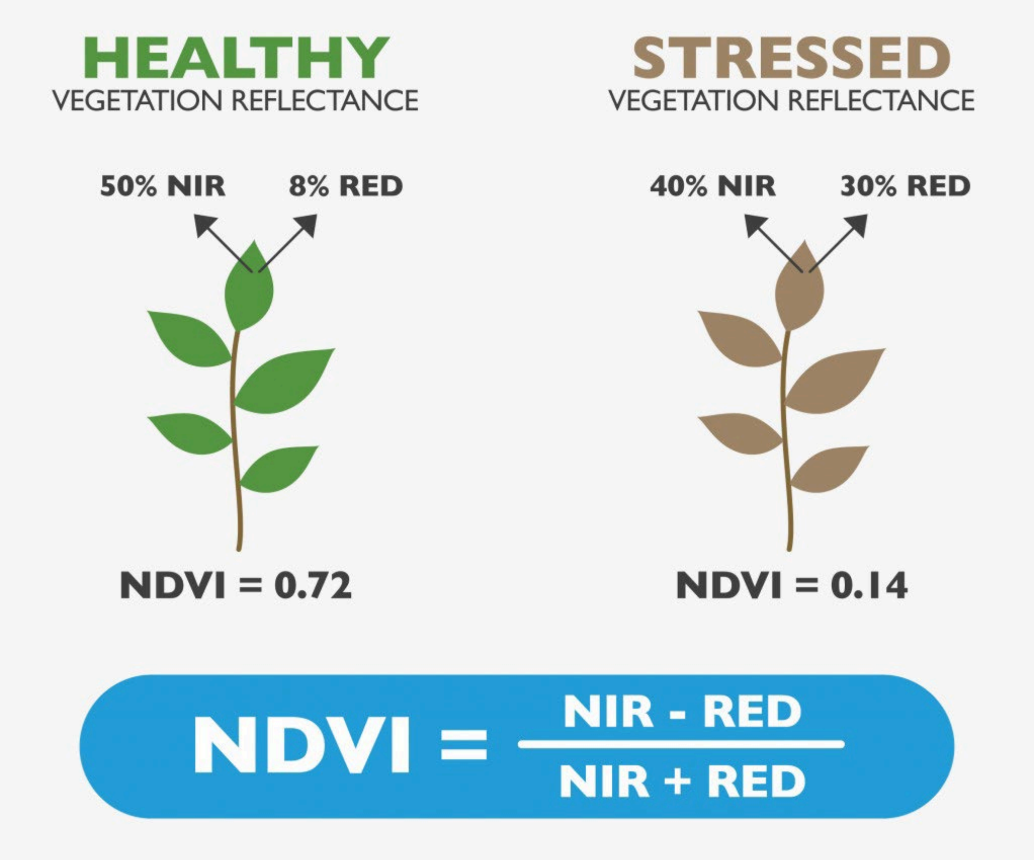
Introduction: Satellite Remote Sensing

- **Satellite Remote Sensing** is the process of accruing information about an object or phenomenon by measuring its reflected and emitted radiation without making physical contact at a distance (typically, from satellite).





Introduction: Healthy vs stressed vegetation



Remote Sensing satellite

Landsat-8

- ❑ NIR: Near Infrared band
- ❑ RED: Red band

- ❑ NDVI: Normalized Differential Vegetation Index

Introduction: Aim and Objectives

- This study outlines a practical approach for assessing plant health and monitoring the agricultural drought using multispectral satellite data.

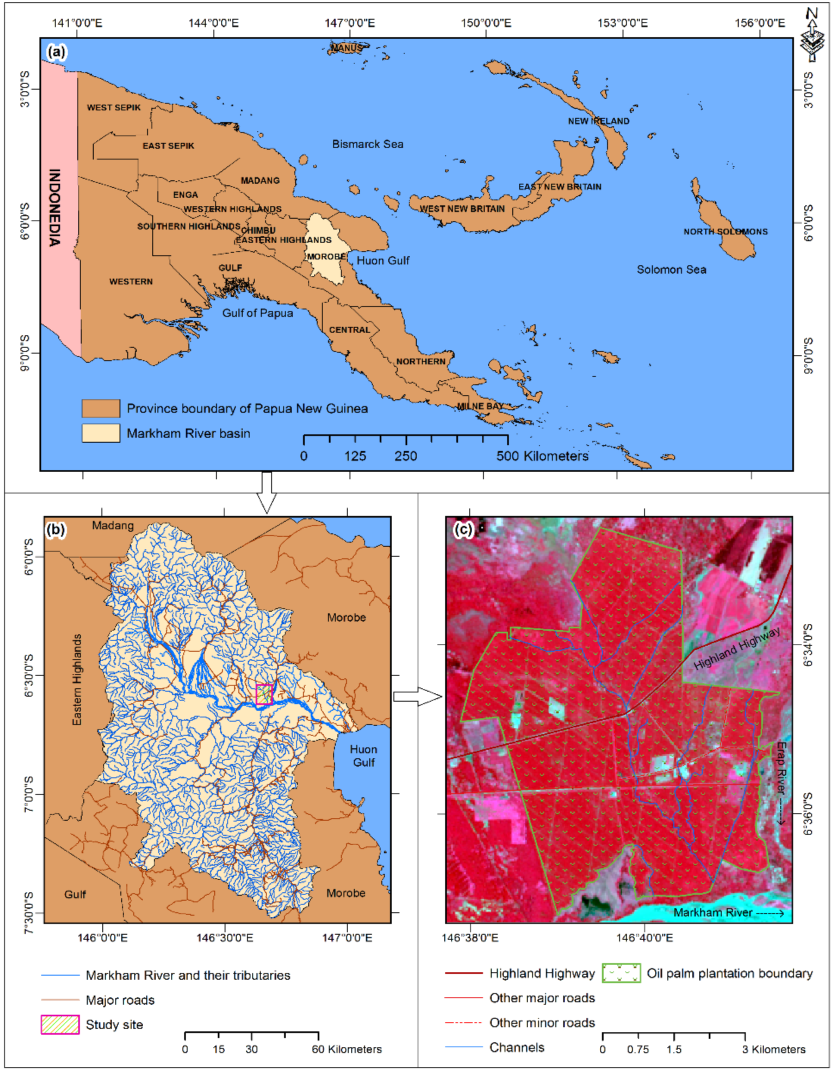
- <u>Objectives</u>
  - Calculate normalized differential vegetation index (NDVI) and land surface temperature (LST) from Landsat satellite image.
  - Conduct temperature dryness vegetation index (TDVI) analysis based on NDVI and LST.
  - Carry out temperature condition index (TCI) analysis based on LST.
  - Perform vegetation condition index (VCI) analysis based on NDVI.
  - Conduct the vegetation health index (VHI) analysis to identify and monitor the health and growth condition of the plantation,

<u>Finally</u>.....

- Comparing drought patterns modeled through TDVI and VHI.

Case study: Site location

- An agricultural site at Erap, dominated by Oil palm plantations.
- Situated on the north bank of the Markham River (Markham Watershed, Morobe, Papua New Guinea)
- The Erap River borders the study site to the east and Markham River to the south.
- Area: 3195 hectare (~32 sq km)
- Plantation Age: 7 years



Introduction: Landsat 8 Satellite Overview

Band number with descriptions	Sensor	Spectral bandwidth (µm)	Spatial resolution (m)
1st band: Coastal Aerosol	LOI	0.43 to 0.45	30
2nd band: Blue		0.450 to 0.51	
3rd band: Green		0.53 to 0.59	
4th band: Red		0.64 to 0.67	
5th band: Near-Infrared		0.85 to 0.88	
6th band: Short-wave Infrared 1		1.57 to 1.65	
7th band: Short Wave Infrared 2		2.11 to 2.29	
8th band: Panchromatic (PAN)		0.50 to 0.68	15
9th band: Cirrus		1.36 to 1.38	30
10th band: Thermal Infrared 1	TIRS	10.6 to 11.19	100
11th band: Thermal Infrared 2		11.5 to 12.51	

Materials used: Satellite data and Parameters

- ❑ Landsat 8 satellite image (03.04.2024) – NIR and RED bands of the operational land imager (OLI) and 10th band of a thermal infrared sensor (TIRS).

- ❑ NDVI: Normalized differential vegetation index using OLI bands
- ❑ LST: Land surface temperature using OLI & TIRS bands
- ❑ VCI: Vegetation Condition Index based on NDVI
- ❑ TCI: Temperature Condition Index based on LST
- ❑ TDVI: Temperature dryness vegetation Index based on LST & NDVI
- ❑ VHI: Vegetation Health Index based on VCI & TCI

Methodology: NDVI Preparation

- The NDVI was calculated through a conventional approach by band ratioing between the near-infrared (NIR) band and red (R) band pixel values.

NDVI = [(near-infrared - Red) / (near-infrared + Red)]

Where NDVI is the normalized differential vegetation index; The near-infrared band is the 5th band and The Red band is the 4th band of Landsat 8 imagery.

Methodology: Land Surface Temperature Model (Huang et al., 2021)

$$\mathrm{TOA\ (L)} = 0.0003342 * \mathrm{Q}cal + 0.1 \quad (1)$$

$$\mathrm{BT} = (1321.0789/(\ln(774.8853/\mathrm{L}) + 1)) - 273.15 \quad (2)$$

$$\mathrm{NDVI} = \mathrm{Float}(\mathrm{NIR}\ band - \mathrm{Red\ band}) / \mathrm{Float}(\mathrm{NIR\ band} + \mathrm{Red\ band}) \quad (3)$$

$$\mathrm{P_v} = \mathrm{Square}\left((\mathrm{NDVI} - \mathrm{NDVI}_{min}) / (\mathrm{NDVI}_{max} - \mathrm{NDVI}_{min})\right) \quad (4)$$

$$\mathrm{E} = 0.004 * Pv + 0.986 \quad (5)$$

$$\mathrm{LST} = (\mathrm{BT} / (1 + (0.00115 * \mathrm{BT} / 1.4388) * \mathrm{Ln(E)})) \quad (6)$$

Where TOA (L) refers to the atmospheric (top) spectral radiance, 0.0003342 is the band-specific multiplicative rescaling factor, 0.1 is the band-specific rescaling factor, Q_{cal} represents the pixel value of the 10^{th} band, BT stands for the brightness temperature, 774.8853 and 1321.0789 are the band-specific thermal conversion constants, L is TOA(L), P_v stands for the proportion of vegetation, E is the emissivity of the land surface,

Methodology: TDVI, dry edge and wet edge (Sandholt et al., 2002)

$$TDVI = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \quad (7)$$

$$LST_{max} = a + b \times NDVI \quad (8)$$

$$LST_{min} = c + d \times NDVI \quad (9)$$

Where LST_{max} and LST_{min} define the dry edge and the wet edge condition of land surface temperature.

The dry edge equation (equation 8) and wet edge equation (equation 9) are determined through the regression analysis (linear); a, b, c, and d are the respective fitting coefficients.

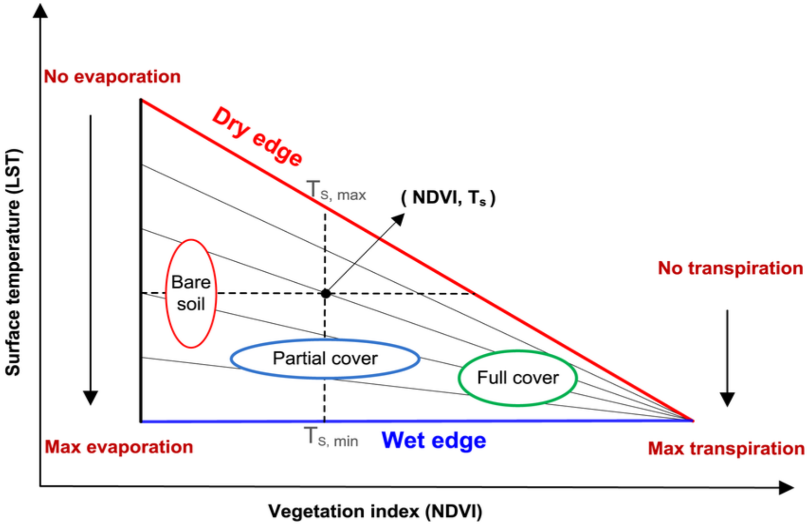
Fitting coefficients are a= 33.993; b= -1.8294; c= 9.2167 and d= 12.279

Methodology: Wet edge and Dry edge

The dry edge (upper fitted) and wet edge (lower fitted) lines were obtained through linear regression analysis between LST and NDVI.

The vegetation characteristics at the upper limit (warm edge) indicate soil conditions without moisture or dryness.

The vegetation characteristics at the bottom (wet edge) indicate very wet soil.



LSTmax /LSTmin	Linear regression
Dry edge (Upper fitted line)	y = -1.8294x + 33.993
Wet edge (lower fitted line)	y = 12.279x + 9.2167

Methodology: VCI, TCI, and VHI *(Rojas et al., 2011; Gidey et al., 2018)*

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} x100 \quad (10)$$

$$TCI = \frac{LST_{min} - LST}{LST_{max} - LST_{min}} x\,100 \quad (11)$$

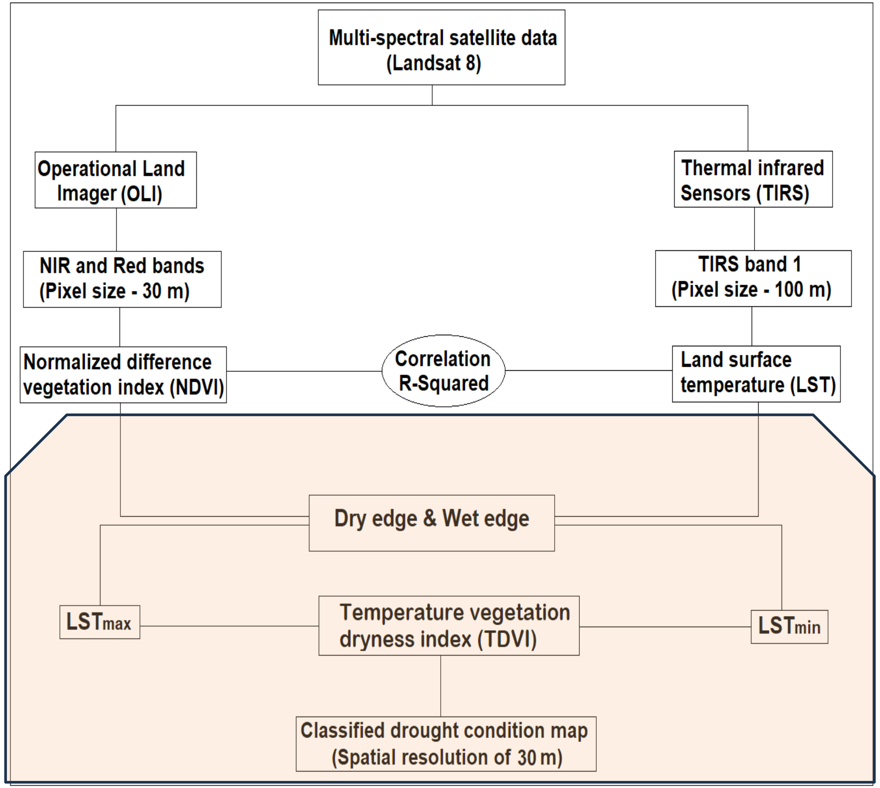
$$VHI = a \times VCI + (1 - a) \times TCI \quad (12)$$

Where VCI represents the vegetation condition index, NDVI stands for normalized differential vegetation index, TCI represents the temperature condition index, VHI stands for vegetation health index,

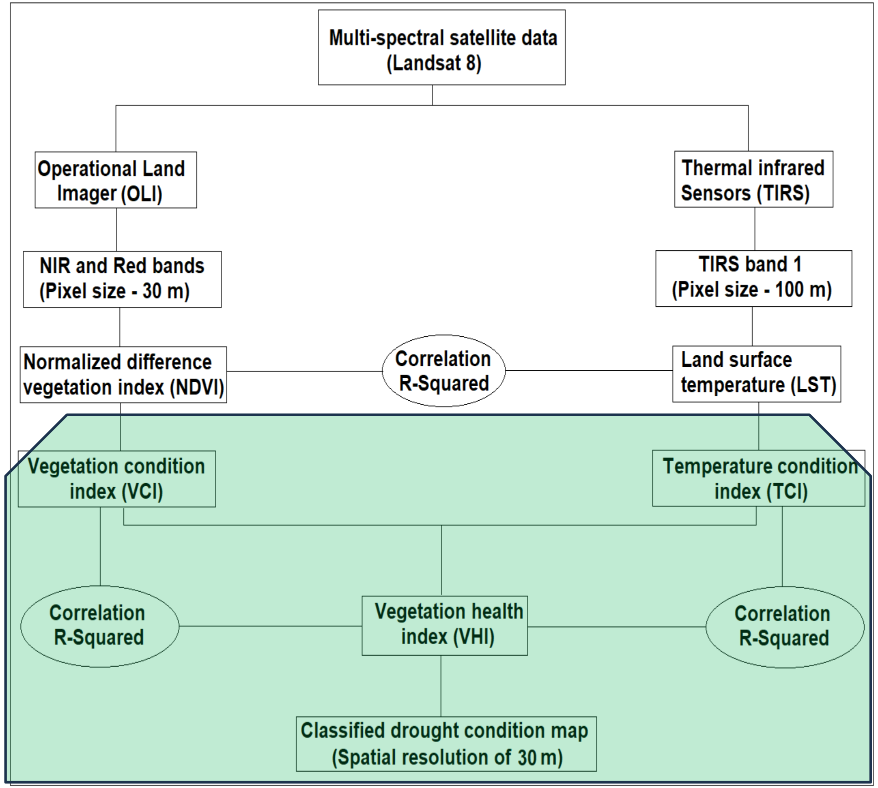
0.5 is a coefficient value for a that regulates the combinations of the VCI and the TCI to the VHI *(Rojas et al., 2011)*.

Methodology: Methodological flow chart

TDVI



VHI



Results: NDVI and LST

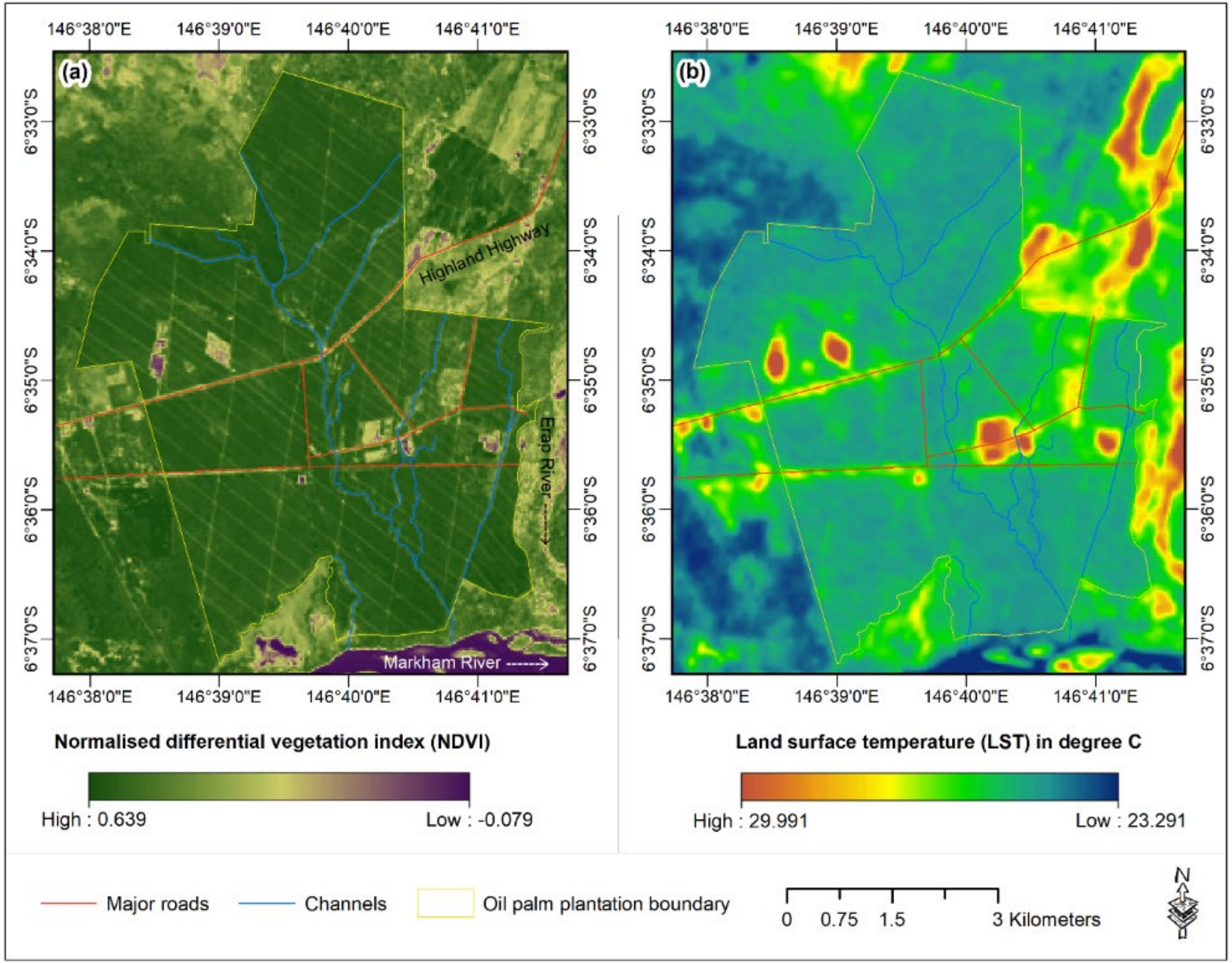
- ❑ NDVI characterizes the phenology of vegetation, with positive values indicating healthy and dense vegetation, and negative values representing water and wetland areas.
- ❑ The output NDVI value is ranged from -0.079 to 0.639.
- ❑ The land surface temperature indicates the level of heat present on the land.
- ❑ The modeled LST is varied from 23.29^{o} C to 29.99^{o} C.

Results: NDVI and LST factors

Resulting database

(a) NDVI and
(b) LST

Based on near-infrared, red, and thermal bands of OLI and the 10th band of the TIR sensor of Landsat 8



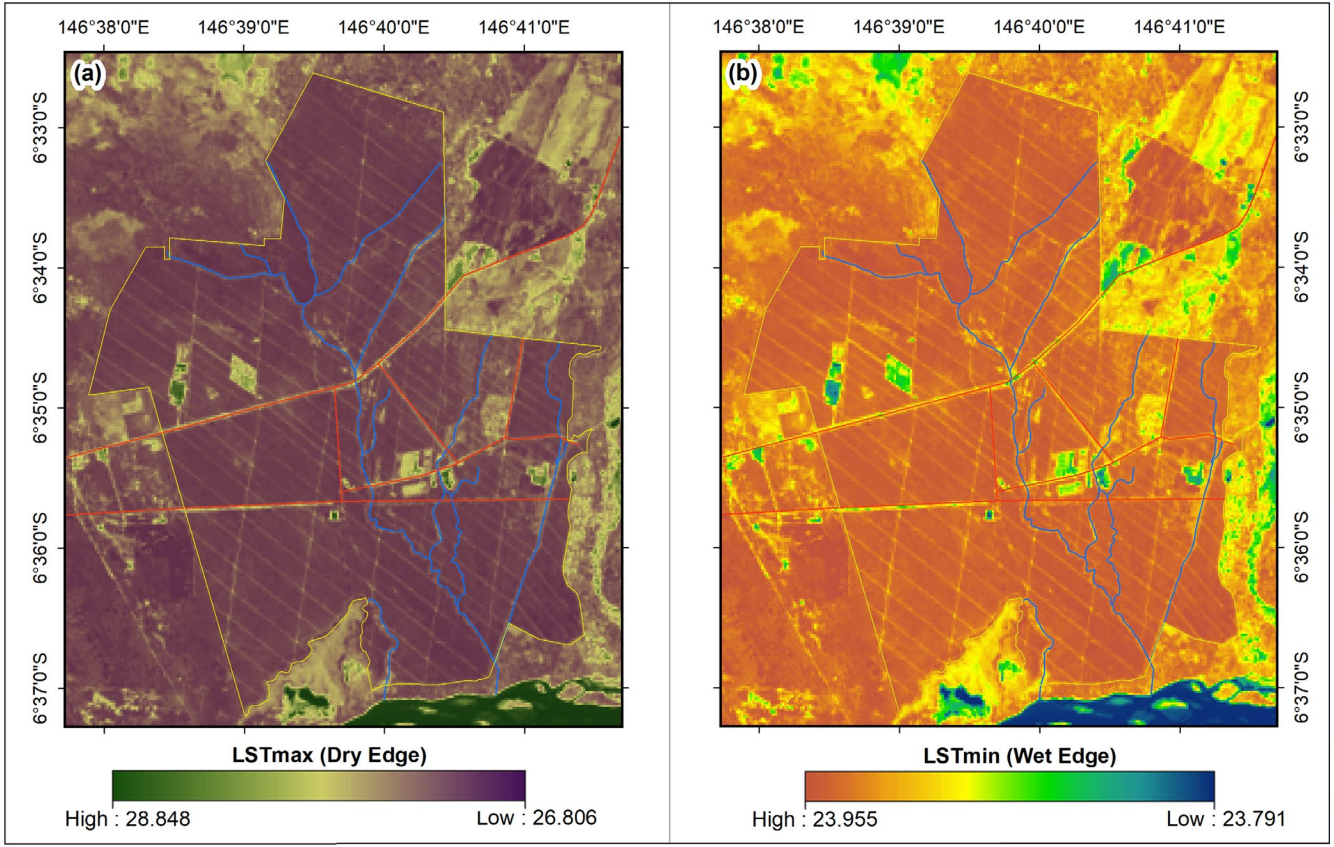
Results: Dry edge and Wet edge

Resulting database

(a) Dry edge derived from NDVI-LST

&

(a) Wet edge derived from NDVI-LST



Results: TDVI

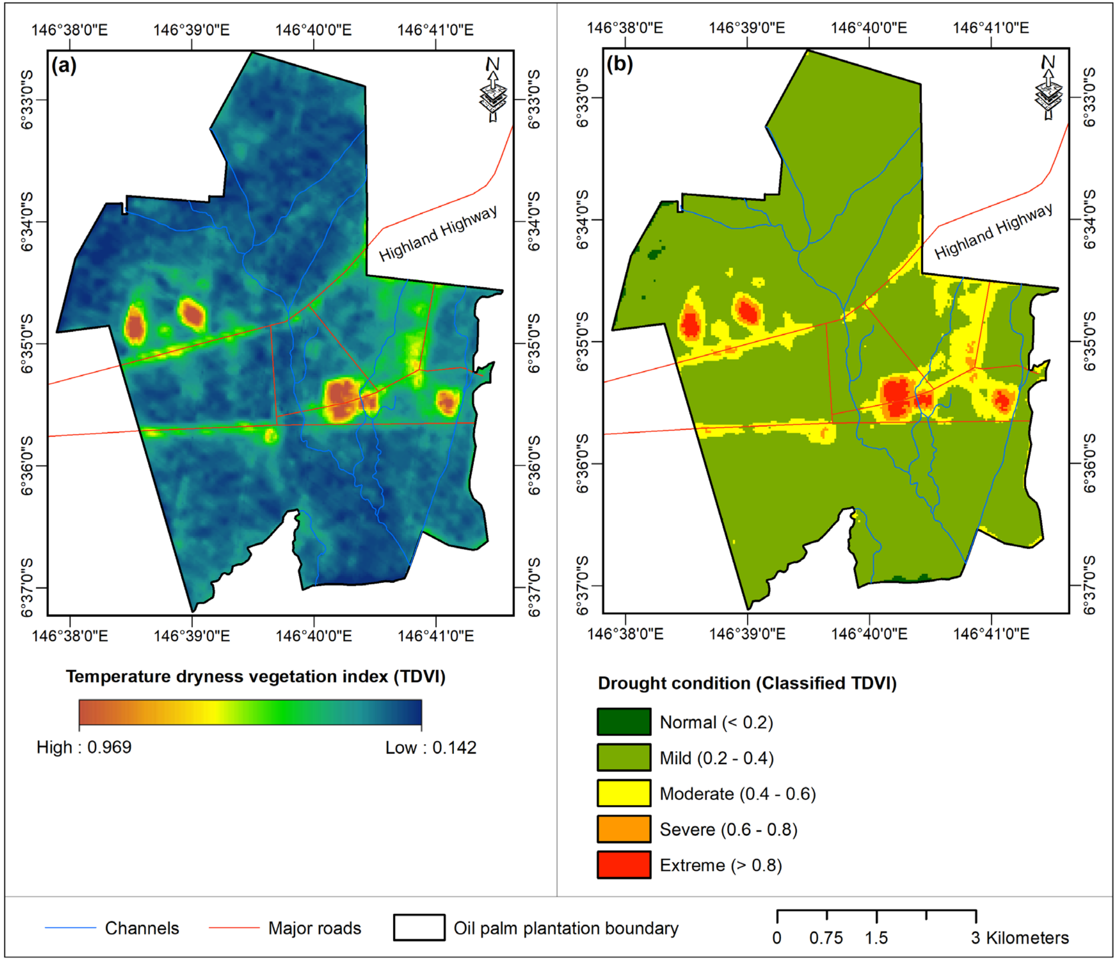
- ❑ In this case study, the TDVI output value ranged from 0.142 to 0.969.
- ❑The complete range of TDVI is divided into five categories, specifically
  - (i) Normal condition (<0.2),
  - (ii) Mild condition (0.2 – 0.4),
  - (iii) Moderate condition (0.4 – 0.6),
  - (iv) Severe condition (0.6 – 0.8), and
  - (v) Extreme condition (>0.8)

Results: TDVI

(a)TDVI value range to show the degree of dryness conditions,

and

(b) classified TDVI to represent the nature of drought conditions



Results: VCI and TCI

- The computed VCI values ranged between 0 and 100.
- VCI range from

50 to 100 signifies vegetation conditions above normal,

50 and 35 indicate mild drought conditions, and

below 35 indicates a severe drought situation.

- The calculated TCI in the site ranges from 0 to 99.99.
- A TCI value of 0 indicates extremely unfavorable conditions, and a value close to 100, represents optimal conditions.

Results:

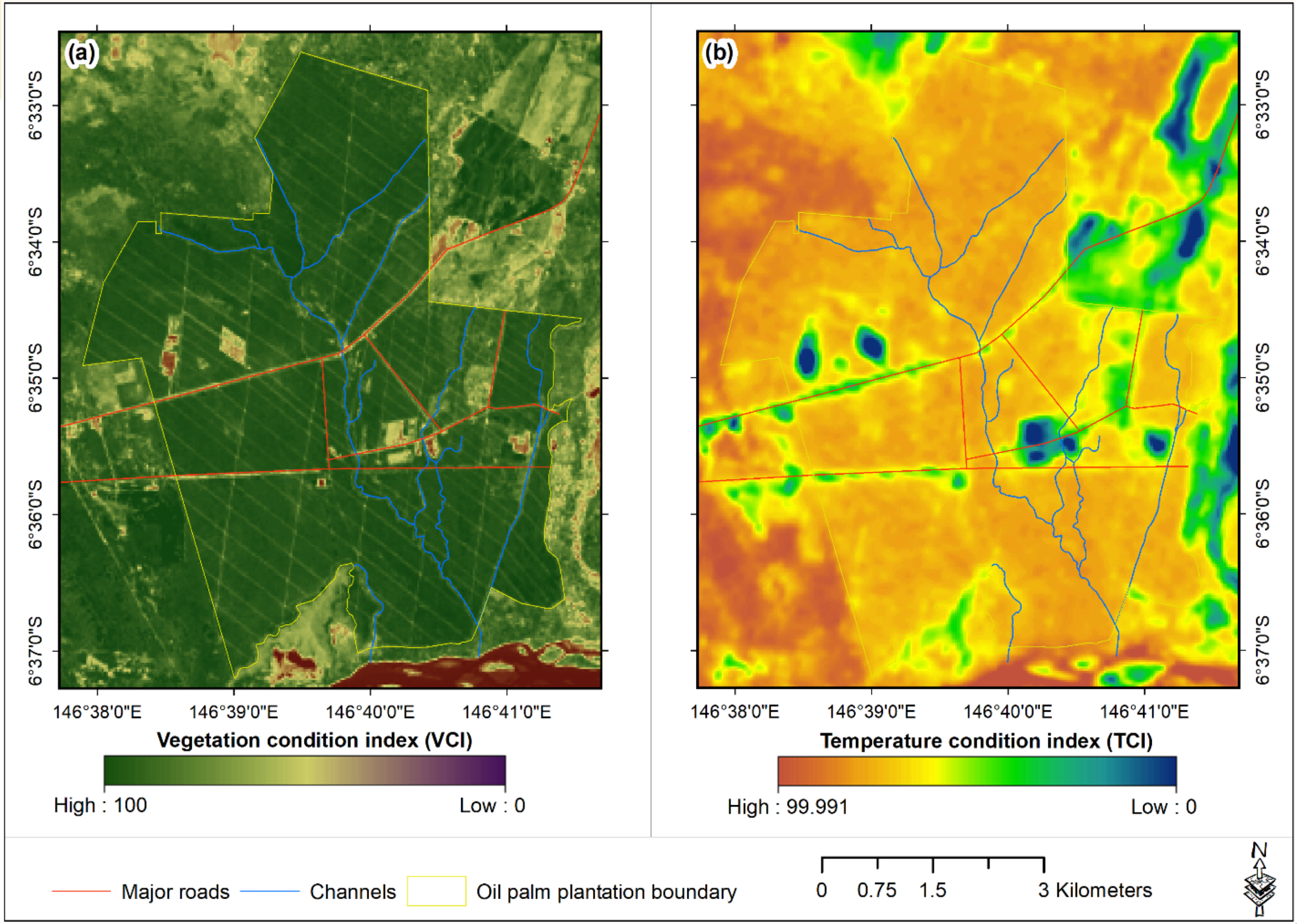
VCI & TCI factors

Resulting database

(a) VCI derived from NDVI

&

(a) TCI derived from LST



Results: VHI

- In this case study, the VHI output ranged from 11.832 to 87.781.

- The complete range of VHI is divided into five categories, specifically

(i) Normal condition (> 80),

(ii) Mild condition (60 - 80),

(iii) Moderate condition (40 – 60),

(iv) Severe condition (20 - 40), and

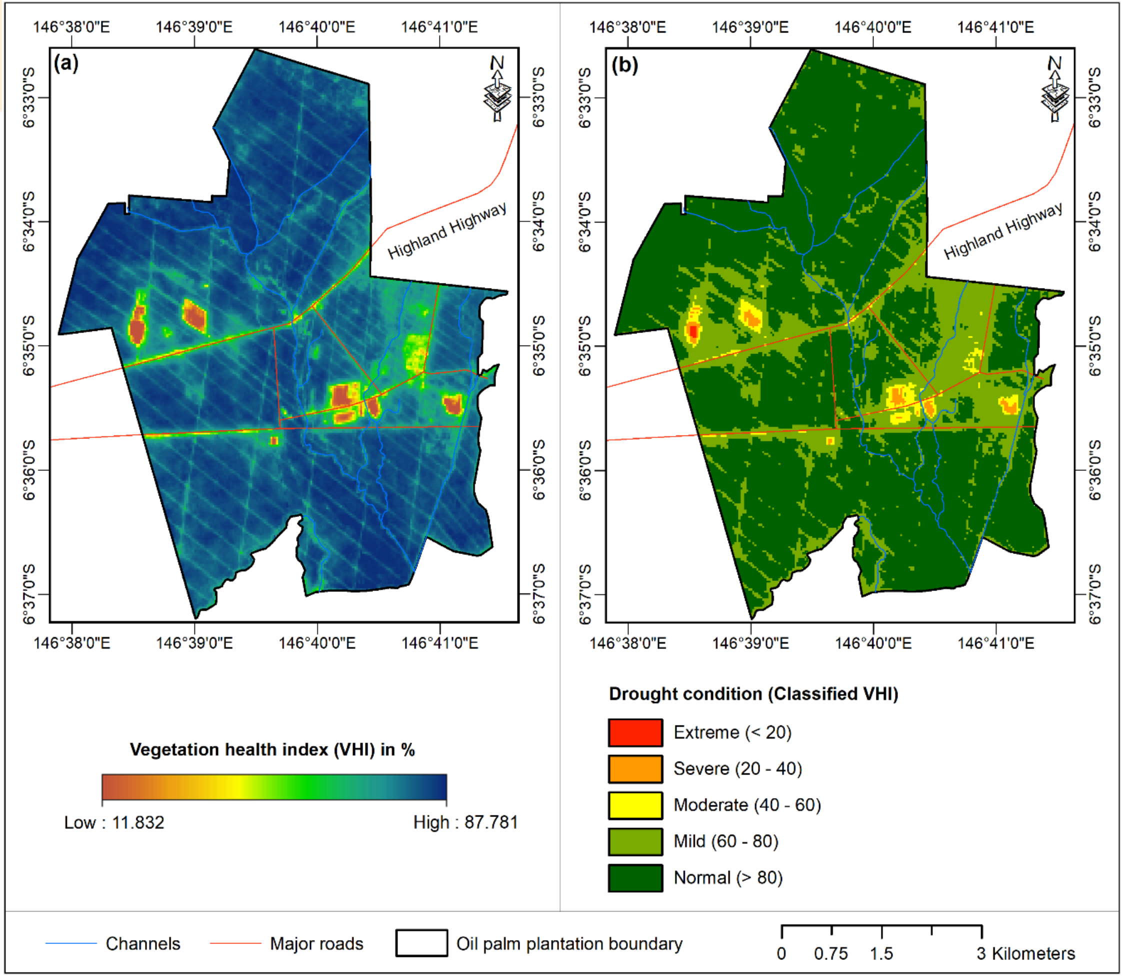
(v) Extreme condition (<20)

Results: VHI

(a)VHI value range to show the degree of health conditions,

and

(b) classified VHI to represent the nature of vegetation health condition

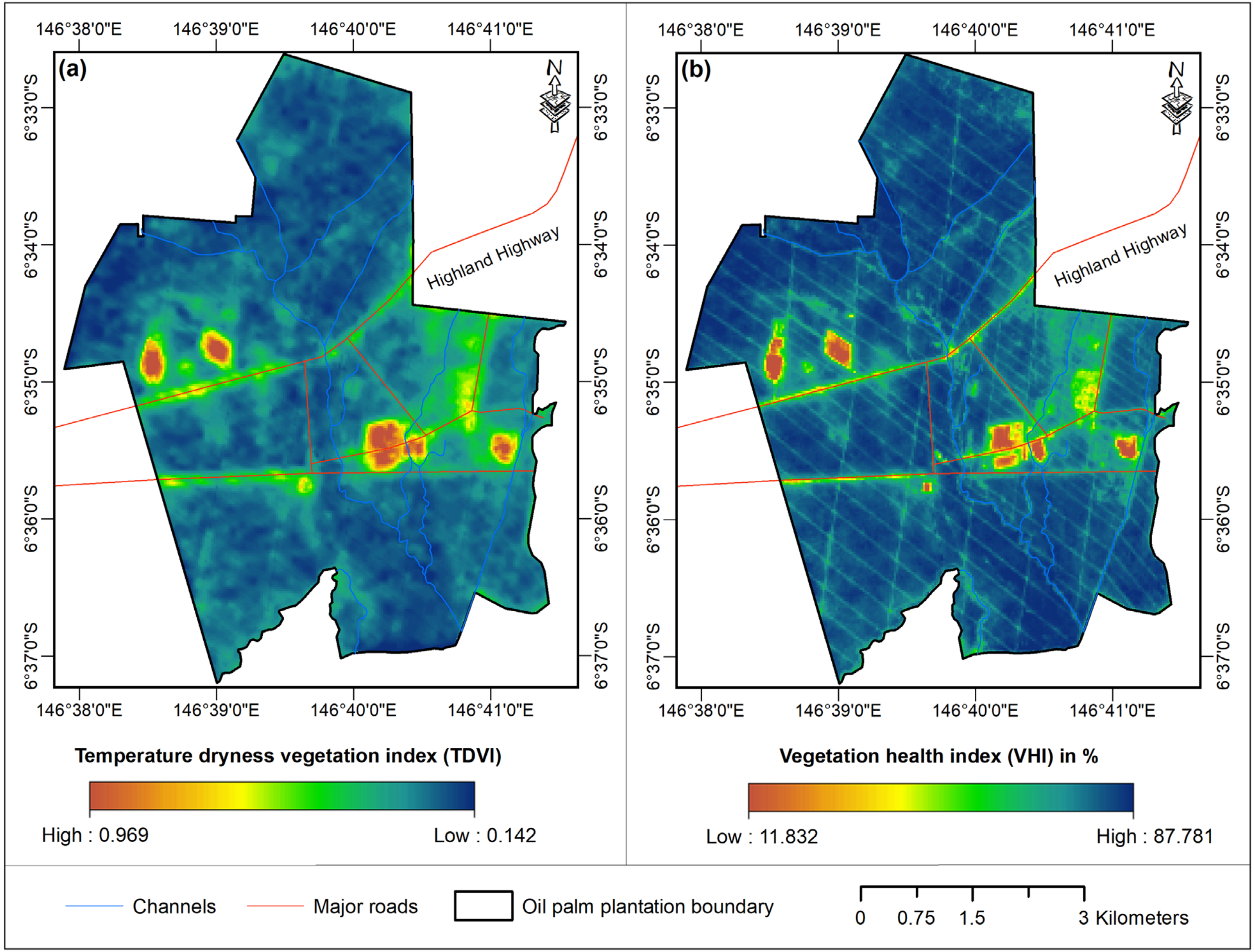


Discussion

- TDVI and VHI, both are calculated from satellite image-driven NDVI and LST.
- The resulting LST data are calculated in a narrow range as the area is characterized as a homogeneous landscape.
- NDVI is sensitive and changes with the fluctuation of soil moisture levels in the agriculture zone.
- A moderate negative correlation (R-square of 0.59) is computed between NDVI and LST, indicating that as the vegetation index decreases, the surface temperature tends to increase.

Discussion: TDVI vs VHI

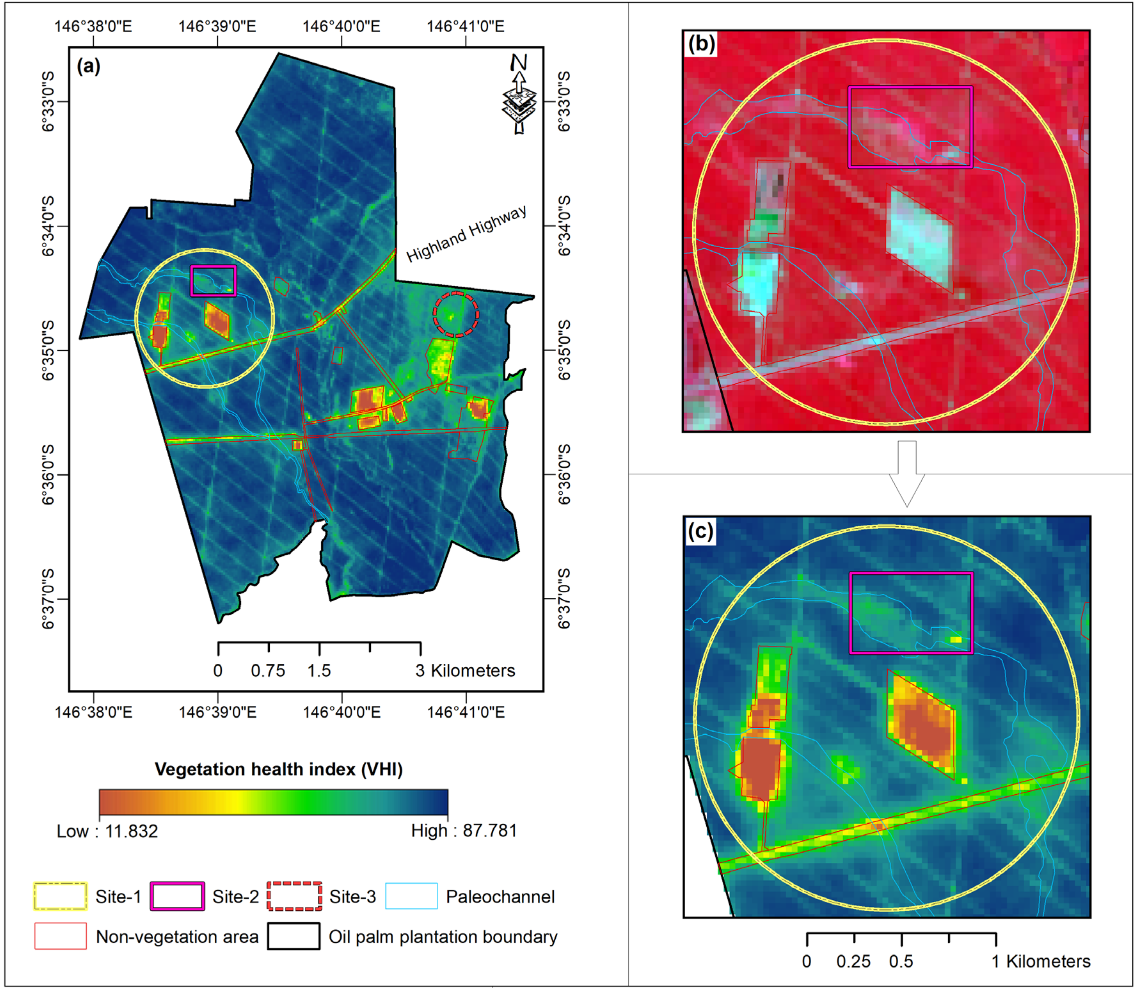
VHI produces details of spatial variation of drought compared to the **TDVI**



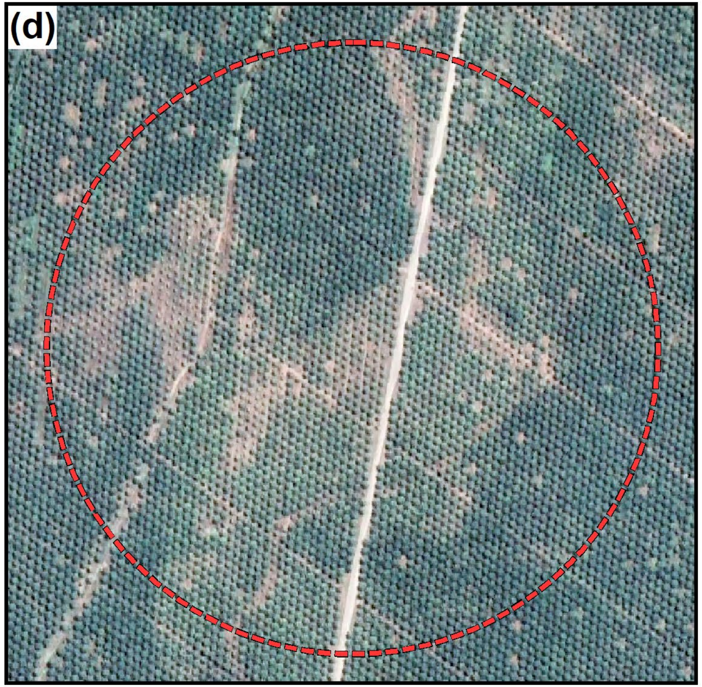
Discussion: VHI

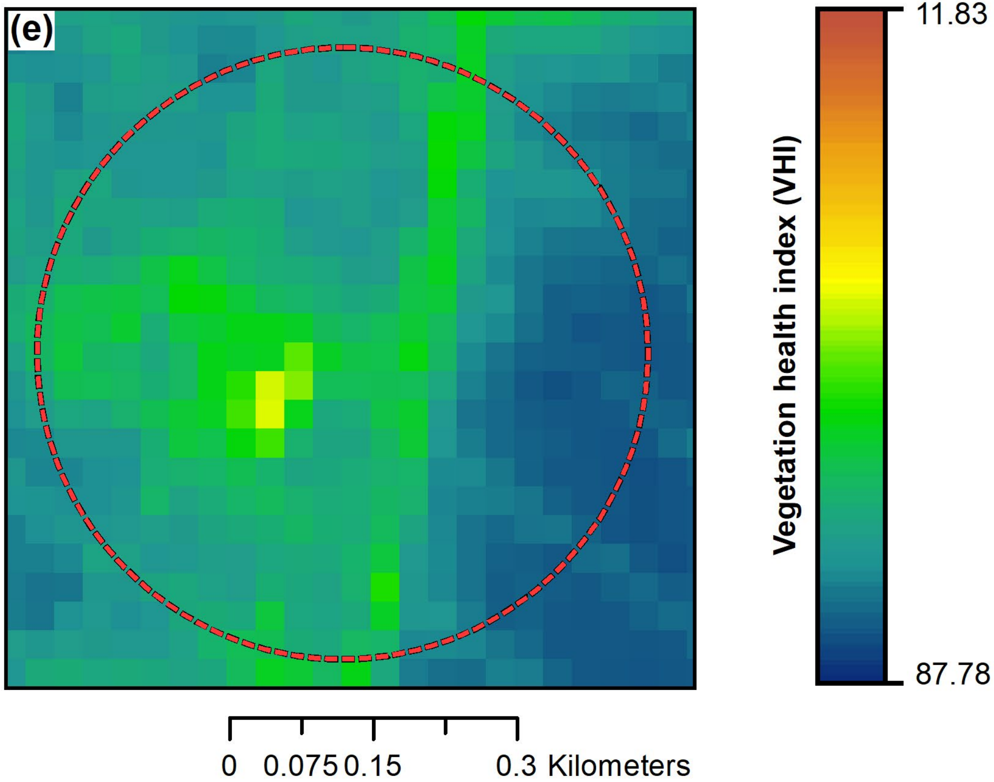
Detailed VHI results compared with the LANDSAT DATA 30m

The resulting VHI is compared at the three sites with real ground features, such as farm buildings, access roads inside the plantation, and paleochannels.

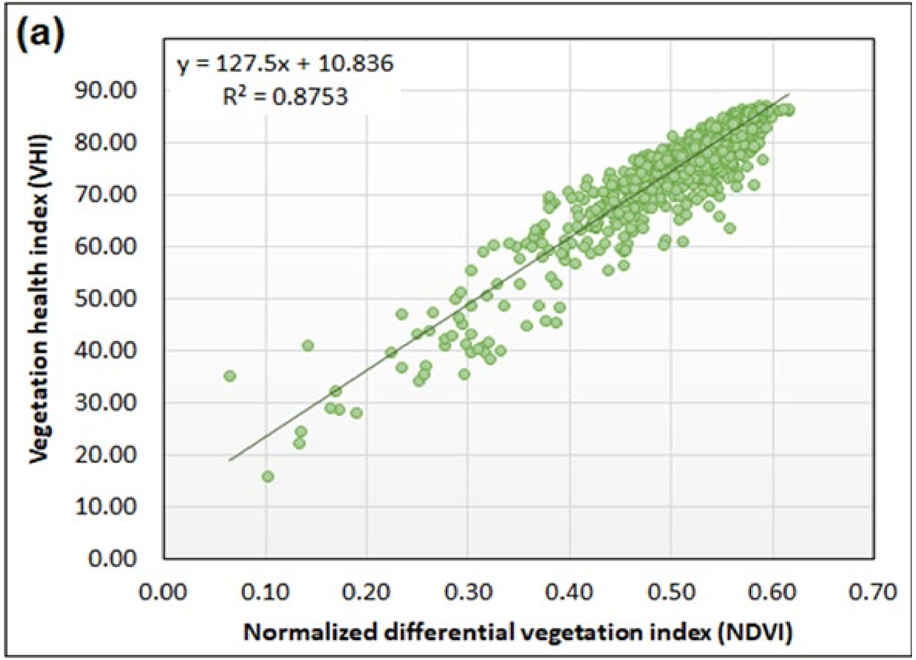


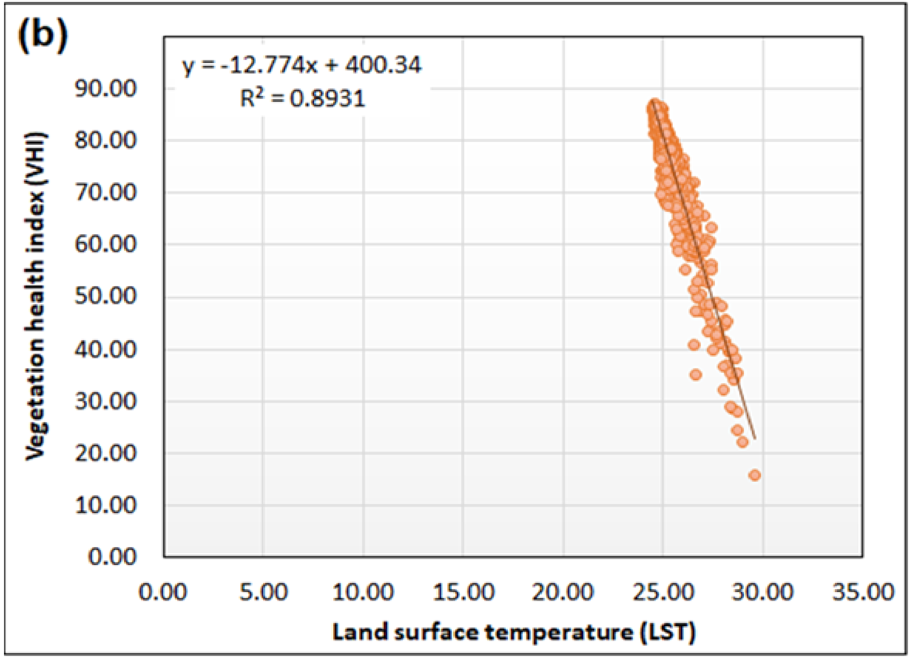
Results: VHI vs High-resolution Aerial Image





Discussion: NDVI-VHI & LST-VHI





- $R^2 = 0.88$ between NDVI and VHI;
- NDVI is the major factor in assessing vegetation health

- $R^2 = 0.89$ between LST and VHI;
- Vegetation health decreases with increased surface temperature

Conclusion

- The VHI accurately depicts the drought situation compared to the TDVI.
- The strong correlations *(R^2 more than 0.88)* indicate that NDVI and LST are the major influencing factors in assessing vegetation health and drought.
- Both the VCI and the TCI are significant in the calculation of VHI.
- They may be influenced by various climatic and environmental variables, which are not considered in this case study.

Recommendation and future work….

- A satellite-based drought model with the inclusion of high-resolution satellite-based precipitation data can generate accurate and dependable drought information systems for large catchment areas.
- **Further research is suggested** by including high-resolution soil moisture data, which will take care of the precipitation factor.
- Additionally, the use of high-resolution multispectral satellite or data will enhance the certainty of prediction.

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Any questions?