Temporal Analysis of High-Canopy Mangrove Forest Based on Remote Sensing Images

A Case Study of Dongzhai Harbor Mangrove Forest, 2018-2024

weishan luo/ spacial ecology in R

CONTENTS

Objectived

Methods

Results

Conclusion

Background

●Dongzhai Harbor is one of the largest mangrove reserves on China's northern tropical coast.

●It's a large-scale mangrove area situated at the northern edge of the tropical zone in China, making it unique and vulnerable to environmental changes.

●The area is significantly influenced by tides and sediment deposition, which are key factors affecting mangrove health and growth.

Background

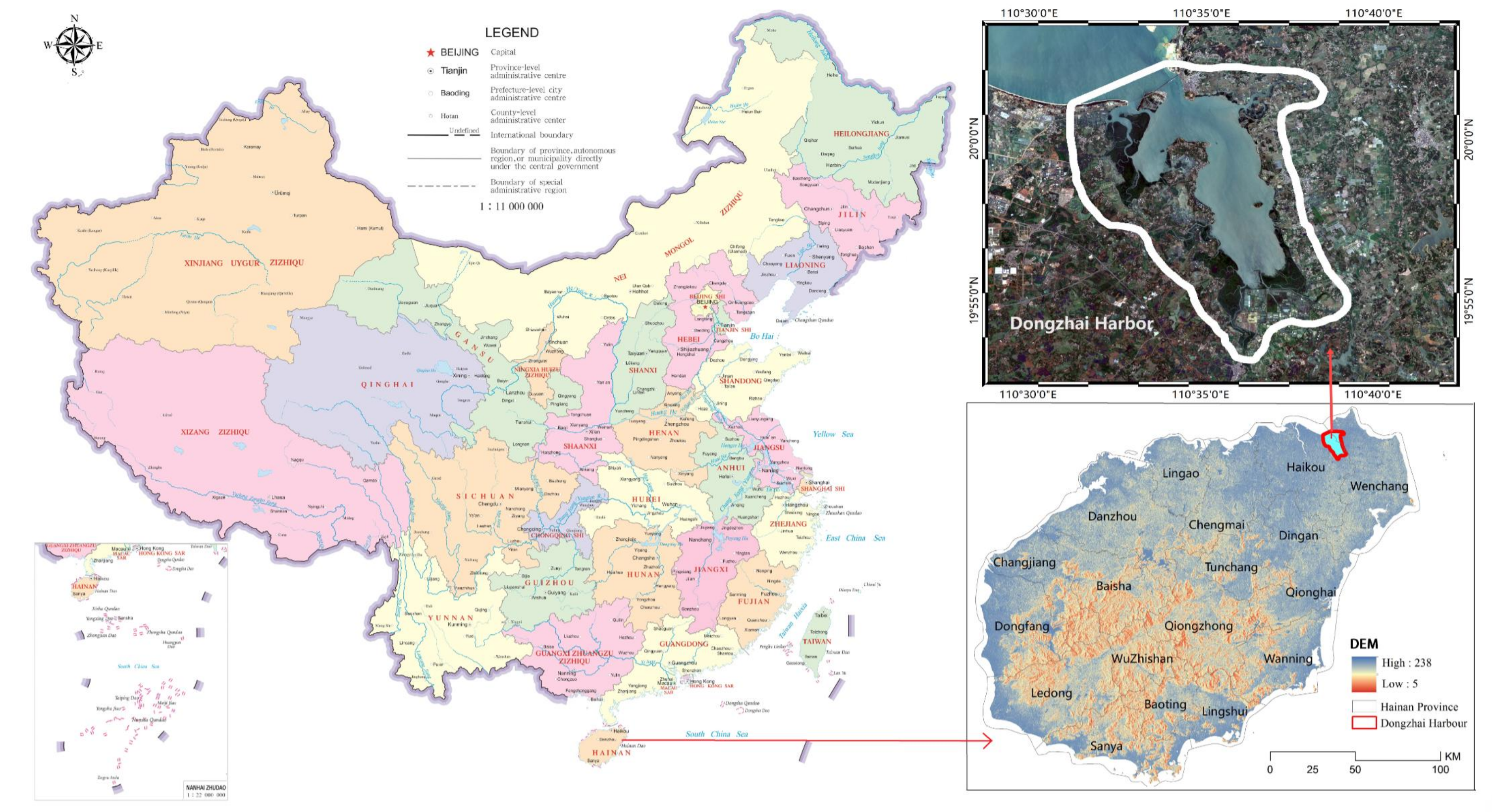


Fig. 1. Location of Dongzhai Harbor.

Area of study:
1,578 hm²

Period:
2018-2024

Objective

- Compare the area change of high-canopy vegetation (NDVI ≥ 0.50) in the study area between 2018, 2020, 2022, 2024.

- Analyze vegetation dynamics during different periods, identifying areas of gain, loss, and stability.

CONTENTS

Objectived

Methods

Results

Conclusion

Data Source

- Sentinel-2 satellite images (from 2018-2024):

    Red bands (B04)

    Near-Infrared bands (B08)

- Downloaded from the Copernicus Browser.

Analysis Workflow

1. Import image bands.
2. Calculate NDVI using the formula: $NDVI = \frac{NIR - RED}{NIR + RED}$
3. Create binary masks using a threshold (NDVI ≥ 0.50).
4. Calculate the total area of the high-canopy vegetation.
5. Perform raster overlay analysis to generate a change map (Loss/Gain/Stable/Other).

CONTENTS

Objectived

Methods

Results

Conclusion

1.Setup & Data Loading

```r
# Load the terra package for raster data processing
library(terra)

# Set the data directory path
data_dir <- "C:/Users/罗伟珊/Documents/R/mangrove_data"

# ---- 2018 ---- #
# Construct file paths for the 2018 bands
path_b04_2018 <- file.path(data_dir, "DZ_2018_B04.tif")
path_b08_2018 <- file.path(data_dir, "DZ_2018_B08.tif")
# Read the B04 (Red) and B08 (NIR) bands into R
b04_2018 <- rast(path_b04_2018)
b08_2018 <- rast(path_b08_2018)

# ---- 2020 ---- #
# Construct file paths for the 2020 bands
path_b04_2020 <- file.path(data_dir, "DZ_2020_B04.tif")
path_b08_2020 <- file.path(data_dir, "DZ_2020_B08.tif")
# Read the B04 and B08 bands
b04_2020 <- rast(path_b04_2020)
b08_2020 <- rast(path_b08_2020)
```

1. I started by loading the **terra library** for raster data.

2. Then, I imported the **satellite imagery** data for 2018, 2020, 2022, and 2024, which is the foundation of my project.

1.Setup & Data Loading

```r

# --- 2022 --- #
# Construct file paths for the 2022 bands
path_b04_2022 <- file.path(data_dir, "DZ_2022_B04.tif")
path_b08_2022 <- file.path(data_dir, "DZ_2022_B08.tif")
# Read the B04 and B08 bands
b04_2022 <- rast(path_b04_2022)
b08_2022 <- rast(path_b08_2022)

# --- 2024 --- #
# Construct file paths for the 2024 bands
path_b04_2024 <- file.path(data_dir, "DZ_2024_B04.tif")
path_b08_2024 <- file.path(data_dir, "DZ_2024_B08.tif")
# Read the B04 and B08 bands
b04_2024 <- rast(path_b04_2024)
b08_2024 <- rast(path_b08_2024)

```

2.Calculate NDVI

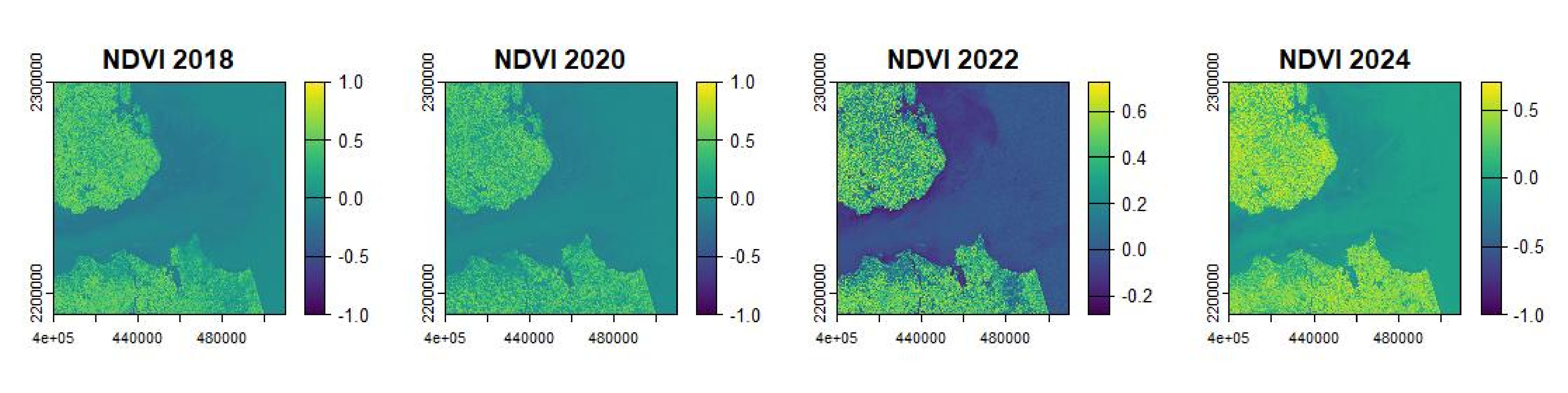
```r
# --- 2018 NDVI Calculation --- #
# DVI: NIR - RED
dvi_2018 <- b08_2018 - b04_2018
# Calculate NDVI
ndvi_2018 <- dvi_2018 / (b08_2018 + b04_2018)

# --- 2020 NDVI Calculation --- #
# DVI: NIR - RED
dvi_2020 <- b08_2020 - b04_2020
# Calculate NDVI
ndvi_2020 <- dvi_2020 / (b08_2020 + b04_2020)

# --- 2022 NDVI Calculation --- #
# DVI: NIR - RED
dvi_2022 <- b08_2022 - b04_2022
# Calculate NDVI
ndvi_2022 <- dvi_2022 / (b08_2022 + b04_2022)

# --- 2024 NDVI Calculation --- #
# DVI: NIR - RED
dvi_2024 <- b08_2024 - b04_2024
# Calculate NDVI
ndvi_2024 <- dvi_2024 / (b08_2024 + b04_2024)

# Create a 2x2 plotting layout
par(mfrow = c(2, 2))

# Plot each year's NDVI image
plot(ndvi_2018, main = "NDVI 2018")
plot(ndvi_2020, main = "NDVI 2020")
plot(ndvi_2022, main = "NDVI 2022")
plot(ndvi_2024, main = "NDVI 2024")
```

1. In this step, I calculated the **NDVI (Normalized Difference Vegetation Index).**

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

2. Using satellite band data, I measured the **health** and **density** of the mangrove forest for each year.

2.Calculate NDVI



- **Yellow/Green Represents Healthy Vegetation:** The yellow and green areas in the images indicate dense, healthy vegetation with **high** NDVI values.

- **Blue/Purple Represents Non-Vegetation:** The blue and purple areas represent rivers, water bodies, or bare ground with **low** NDVI values.

Visually, a comparison of the images shows that the coverage of the **yellow/green areas expanded annually**, indicating an apparent **continuous increase** in the area of high-canopy vegetation at Dongzhai Harbor Mangrove Forest.

3.Thresholding & Area Calculation

```
# Set the NDVI threshold
thr <- 0.50

# --- Create Masks (TRUE/FALSE) --- #
# Pixels with NDVI >= threshold become TRUE
mask18 <- ndvi_2018 >= thr
mask20 <- ndvi_2020 >= thr
mask22 <- ndvi_2022 >= thr
mask24 <- ndvi_2024 >= thr

# --- Get Pixel Area --- #
# Get the x/y resolution of the raster
res_xy <- res(ndvi_2018)
# Calculate the area of a single pixel
pix_m2 <- res_xy[1] * res_xy[2]
```

1. I used an **NDVI threshold** to differentiate between **high-density vegetation** and **non-high-density vegetation**.

2. Then, I calculated the **total area of high-density vegetation** for each year, with the table showing the specific area data.

3.Thresholding & Area Calculation

```
# --- Calculate Area for All Years --- #
# 2018
vals18 <- values(mask18)
n_true18 <- sum(vals18, na.rm = TRUE)
area18_ha <- n_true18 * pix_m2 / 10000

# 2020
vals20 <- values(mask20)
n_true20 <- sum(vals20, na.rm = TRUE)
area20_ha <- n_true20 * pix_m2 / 10000

# 2022
vals22 <- values(mask22)
n_true22 <- sum(vals22, na.rm = TRUE)
area22_ha <- n_true22 * pix_m2 / 10000

# 2024
vals24 <- values(mask24)
n_true24 <- sum(vals24, na.rm = TRUE)
area24_ha <- n_true24 * pix_m2 / 10000

# Create a data frame to store the results
years <- c(2018, 2020, 2022, 2024)
areas_ha <- c(area18_ha, area20_ha, area22_ha, area24_ha)
results_df <- data.frame(Year = years, Area_ha = areas_ha)

# Print the data frame
print(results_df)
```

3.Thresholding & Area Calculation

This table presents the calculated area of high-NDVI vegetation for each year. While the **visual analysis** suggests a **steady increase** in vegetation, the **quantitative data** shows **significant fluctuations** from year to year.

Year	Area
2018	104897.58
2020	77527.85
2022	109425.03
2024	63740.73

The data from the R output confirms this fluctuation, which contradicts the visual trend. This discrepancy is likely due to the **tidal environment** of the mangrove forest. Satellite images captured during different tidal conditions (high vs. low tide) will show varying amounts of submerged vegetation, directly affecting the calculated NDVI area.

4.Change Map Visualization

```r
# --- Change Map Visualization (2018 vs. 2024) ---

# Combine the two masks to create a change code
# mask18*1 converts TRUE/FALSE to 1/0
# mask24*2 converts TRUE/FALSE to 2/0
# The sum gives four classes: 0 (Other), 1 (Loss), 2 (Gain), 3 (Stable)
code_18_24 <- mask18 * 1 + mask24 * 2

# Choose a custom color palette
my_colors <- c("#F0F0F0", "#D95F02", "#1B9E77", "#6A3D9A") # Light Gray, Orange, Teal, Purple

# Plot the change map with specified colors and breaks
plot(code_18_24,
     col    = my_colors,
     # Set breaks to ensure each integer value (0, 1, 2, 3) gets a unique color
     breaks = c(-Inf, 0.5, 1.5, 2.5, Inf),
     legend = FALSE, # Do not plot the default legend
     main   = paste0("Change 2018→2024 (NDVI ≥ ", thr, ")"))
```

This slide shows how my code creates the change map.

1. I first combined the vegetation masks from 2018 and 2024 to generate a new raster with four distinct categories .
2. Next, I customized a color palette to match the style of my presentation and assigned these colors to the four categories.

- **Other:** Areas that did not meet the NDVI threshold, including **water and bare ground.**
- **Loss:** Areas that changed from healthy vegetation to non-vegetation **(decrease)**.
- **Gain:** Areas that changed from non-vegetation to healthy vegetation **(increase)**.
- **Stable:** Areas that remained healthy vegetation throughout the period **(consistencey).**

4.Change Map Visualization

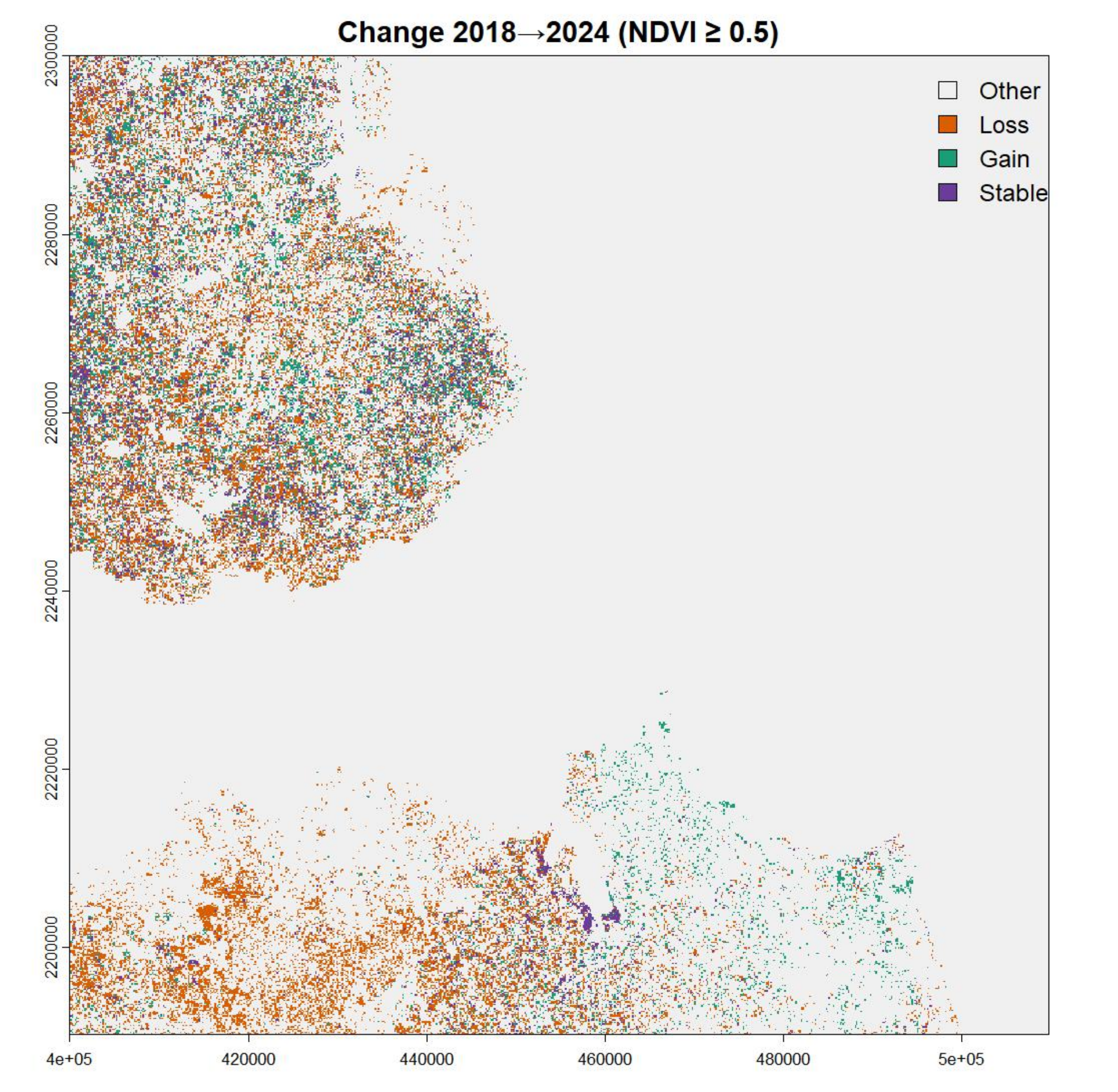
```r
# Plot the change map with specified colors and breaks
plot(code_18_24,
     col    = my_colors,
     # Set breaks to ensure each integer value (0, 1, 2, 3) gets a unique color
     breaks = c(-Inf, 0.5, 1.5, 2.5, Inf),
     legend = FALSE, # Do not plot the default legend
     main   = paste0("Change 2018→2024 (NDVI ≥ ", thr, ")"))

# Add a custom legend
legend("topright",
       # bty="n" removes the box around the legend
       bty="n",
       # Specify fill colors for the legend symbols
       fill   = my_colors,
       # Specify text labels for each color
       legend = c("Other","Loss","Gain","Stable"))
```

This part of the code shows how I visualized the data into the final map.

1. I used the **plot() function** to draw the change map and applied the custom colors and legend I defined.

2. I specifically added a **custom legend** that clearly explains what each color represents, making the map easy to understand.

4.Change Map Visualization



This map shows the **land cover changes** in the Dongzhai Harbor mangrove forest from 2018 to 2024.

Visually, the map shows a significant number of scattered **Gain** (teal) and **Loss** (orange) pixels, indicating that vegetation changes were **widespread** and **not concentrated** in one area.

The **Stable** (purple) pixels appear very **fragmented**, suggesting that few areas maintained consistent, high-density vegetation over the six-year period.

This irregular pattern is likely due to the influence of **tides** on the satellite imagery from different years.

5. Regression Analysis

```r
# ---Regression Analysis ---
# Create a data frame to hold the NDVI area data
# The 'Area_ha' values are based on the previous thresholding calculations.
ndvi_data <- data.frame(
  Year = c(2018, 2020, 2022, 2024),
  Area_ha = c(104898, 77528, 109425, 63741)
)

# 2. Run a linear regression model
# The formula 'Area_ha ~ Year' models Area_ha as a function of Year.
lm_model <- lm(Area_ha ~ Year, data = ndvi_data)

# 3. Print the summary of the model
# The summary provides key statistical information, including the p-value.
summary(lm_model)
```

- To analyze the data more rigorously, I performed a regression analysis.
- This model examined **whether the NDVI area showed a significant linear change over the years.**

5. Regression Analysis

This result powerfully demonstrates that my project found data volatility, not a simple increase in vegetation.

```
Call:
lm(formula = Area_ha ~ Year, data = ndvi_data)

Residuals:
     1      2      3      4 
  2264 -15949  25106 -11421 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  9342451   10206654   0.915    0.457
Year           -4579       5050  -0.907    0.460

Residual standard error: 22590 on 2 degrees of freedom
Multiple R-squared:  0.2913,	Adjusted R-squared:  -0.06309 
F-statistic: 0.822 on 1 and 2 DF,  p-value: 0.4603
```

- The summary table shows a p-value (Pr(>|t|)) of 0.460, which is **much larger than 0.05**.
- This indicates that there is **no statistically significant** linear trend in the NDVI area over the six-year period.

CONTENTS

Objectived

Methods

Results

Conclusion

Conclusion

My project used remote sensing analysis to successfully reveal the complex changes in the Dongzhai Harbor mangrove forest from 2018 to 2024.

Key Findings:

- **Visual vs. Data Contradiction:** While NDVI images visually appeared to show a continuous increase in vegetation, my quantitative analysis—specifically the **p-value (0.460)** from the regression analysis—powerfully demonstrated that there was **no statistically significant linear trend of increase.**

- **The Nature of Fluctuation:** The data's volatility is the central finding of this project. It is primarily caused by environmental factors like **tides**, which affect the NDVI measurements in satellite imagery at different times.

- **Rigorous Analysis:** My research highlights that relying solely on visual judgment is insufficient when analyzing dynamic ecosystems. By combining **quantitative data** and a **deeper understanding of environmental factors**, we can reach truly rigorous and accurate conclusions.

Thank you for the attention!

weishan luo/ spacial ecology in R