



*Fig 1: Pacific slope of Peru and Northern Chile [1]*

# Monitoring Vegetation Trends as a Result of Climate Change

Panos Antonopoulos,  
pa517@cam.ac.uk

# Contents

## Introduction

## Methodology

- Data Acquisition
- Data Processing
- Calculating Correlations

## Results

- Peru & Northern Chile
- California, USA

## Discussion

- Interpretation of Findings
- Next Steps

## Summary

# Introduction – Motivation

The Pacific Slope of Peru and Northern Chile is one of the most climate vulnerable regions in South America [2]

- Home to significant levels of biological endemism [3]
- Major cities depend on its limited water resources [4,5]

Climate change can intensify pressures on:

- Biodiversity
- Resource availability

This makes environmental monitoring increasingly urgent

- So we can understand and predict future impacts on ecosystem services

# Introduction – Background

An effective way to assess ecological impacts is by monitoring vegetation trends through remote sensing

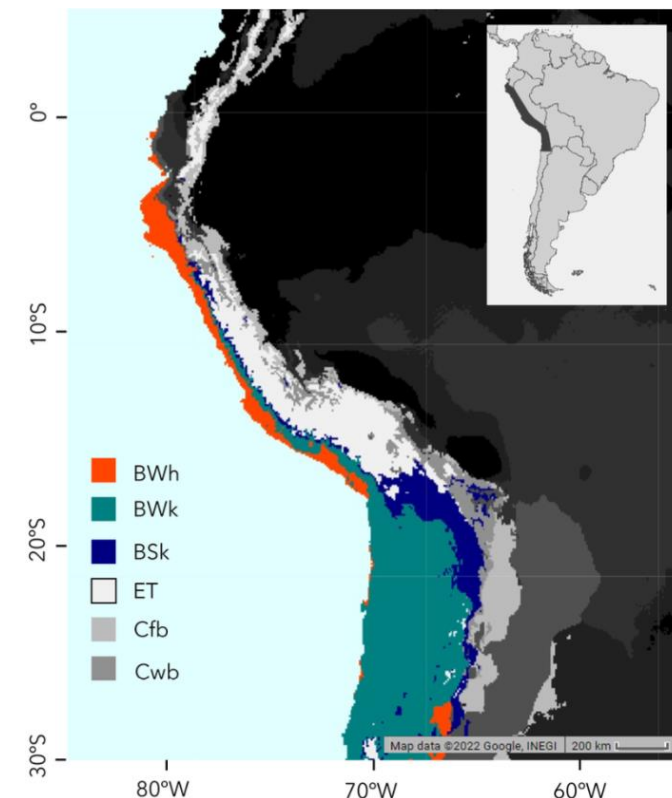
- Using satellite instruments, such as the Moderate Resolution Imaging Spectroradiometer (MODIS)

These instruments provide time series data to evaluate vegetation condition

- In the form of vegetation indices, such as the Enhanced Vegetation Index (EVI)

The Köppen-Geiger (K-G) system is used to contextualise vegetation trends

- The system divides areas into thirty climate zones
- This study focuses on BWh, BWk, and BSk regions



*Fig 1: K-G zones in the study area*

# Introduction – Objectives

The primary objective is to reproduce the original work's findings [6]

- A statistically significant greening strip along the Pacific slope of Peru & Northern Chile
- Correlate EVI time series with CO<sub>2</sub>, Sea Surface Temperature (SST) and Precipitation
- Replication studies are a vital component of the scientific process to verify previous results

The secondary objective is to extend the original work by:

- Developing an open-source pipeline
- Applying it to study California, USA to demonstrate scalability and generality



# Methods – Data Acquisition

The study area was manually defined in Google Earth Pro and imported as a Google Earth Engine (GEE) asset

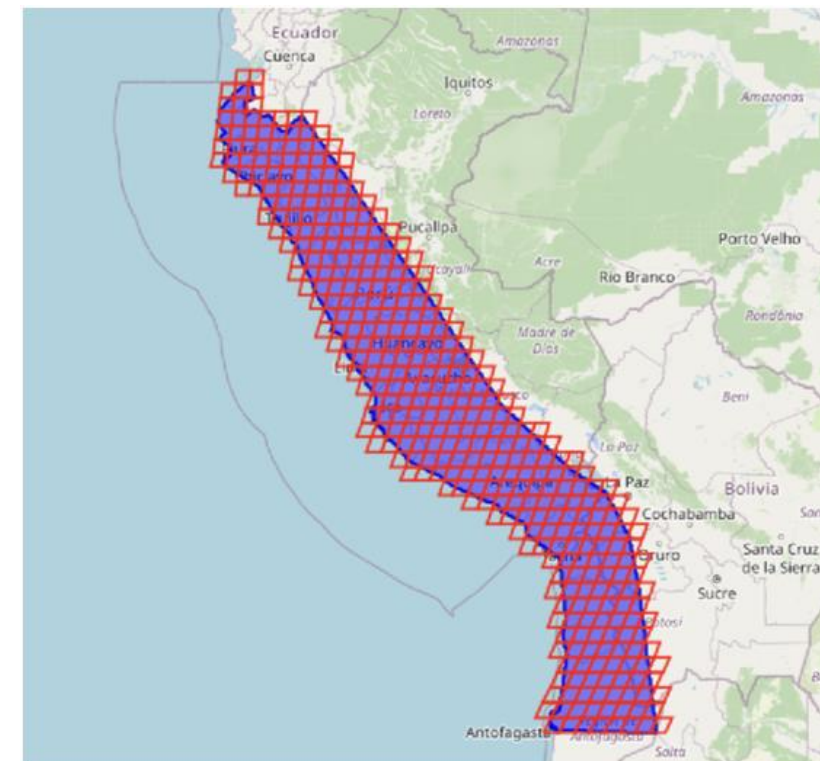


Tiling strategy implemented to divide the study area into smaller, more manageable batches

- Rectangular tiling introduced edge artefacts
- Use native MODIS projection



For each tile, full EVI and Quality Assessment (QA) data were exported to Google Drive for all pixels spanning the 2000-2024 period



*Fig 2: Tiled region in the MODIS projection*

# Methods – Data Processing I

Pixels missing >29.3% of their EVI values were excluded and seasonality was removed from retained pixels

$$F_k = \sum_{i=1}^n |N_i^k - N_i^0| \times W_i$$

Use QA values to mask EVI data that correspond to fill values, snow/ice, and clouds. Again, exclude pixels with >29.3% invalid EVI data

$$W_i = \begin{cases} 1, & \text{when } N_i^0 \geq N_i^{tr} \\ 1 - \frac{d_i}{d_{max}}, & \text{when } N_i^0 < N_i^{tr} \end{cases}$$

Interpolate over masked values ( $N^0$ ), apply Whittaker smoothing ( $N^{tr}$ ), and take the pointwise maximum to create a new series,  $N^I$

$$d_{max} = \max(d_i)$$

$$d_i = |N_i^0 - N_i^{tr}|$$

Iteratively fit  $N^I$  using Savitzky-Golay and take the pointwise maximum to make a new upper envelope. Repeat until fitting index reaches a minimum

Upper Envelope Reconstruction

## Methods – Data Processing II

Output from iterative fitting  
Whittaker smoothed



Use Mann-Kendall test to  
assess statistical significance  
and the slope/intercept of the  
trend



For statistically significant  
pixels, compute  $\Delta_{EVI}$

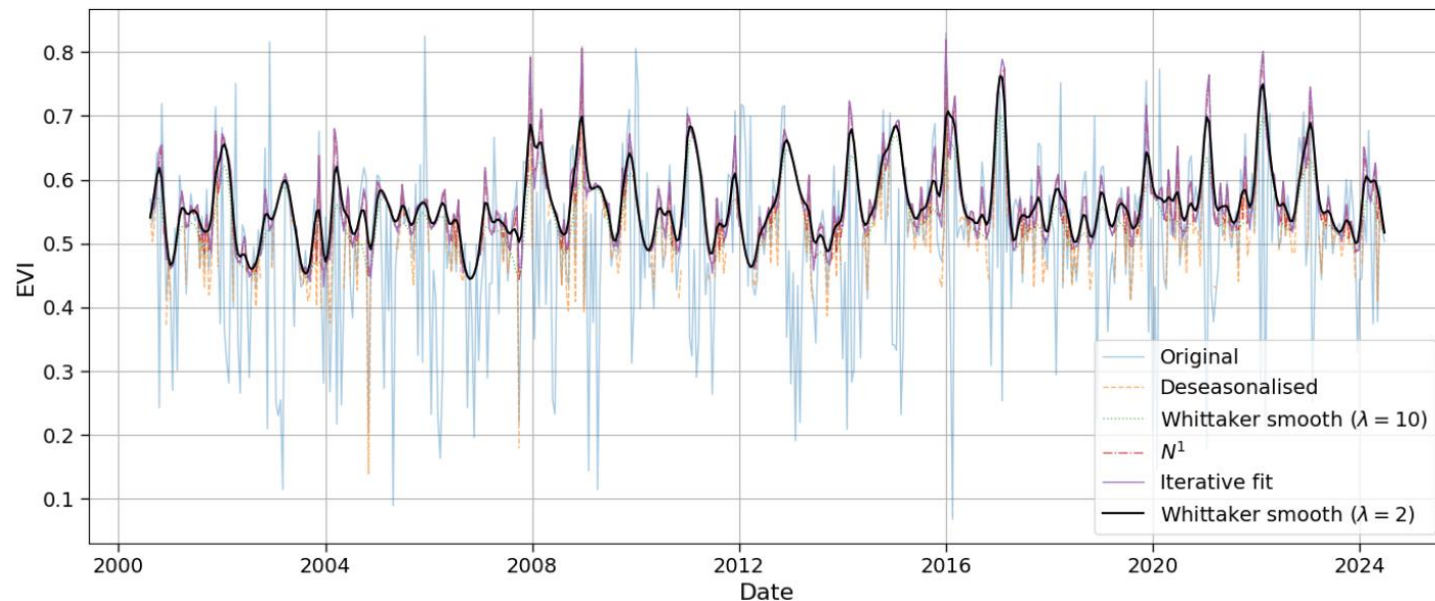


Fig 3: Illustration of time series processing for an arbitrary pixel

$$\Delta_{EVI} = \frac{\text{slope} \times \text{len}(\text{time series}) - 1}{\text{intercept} - \text{slope} \times \text{len}(\text{final series})}$$



# Methods – Calculating Correlations I

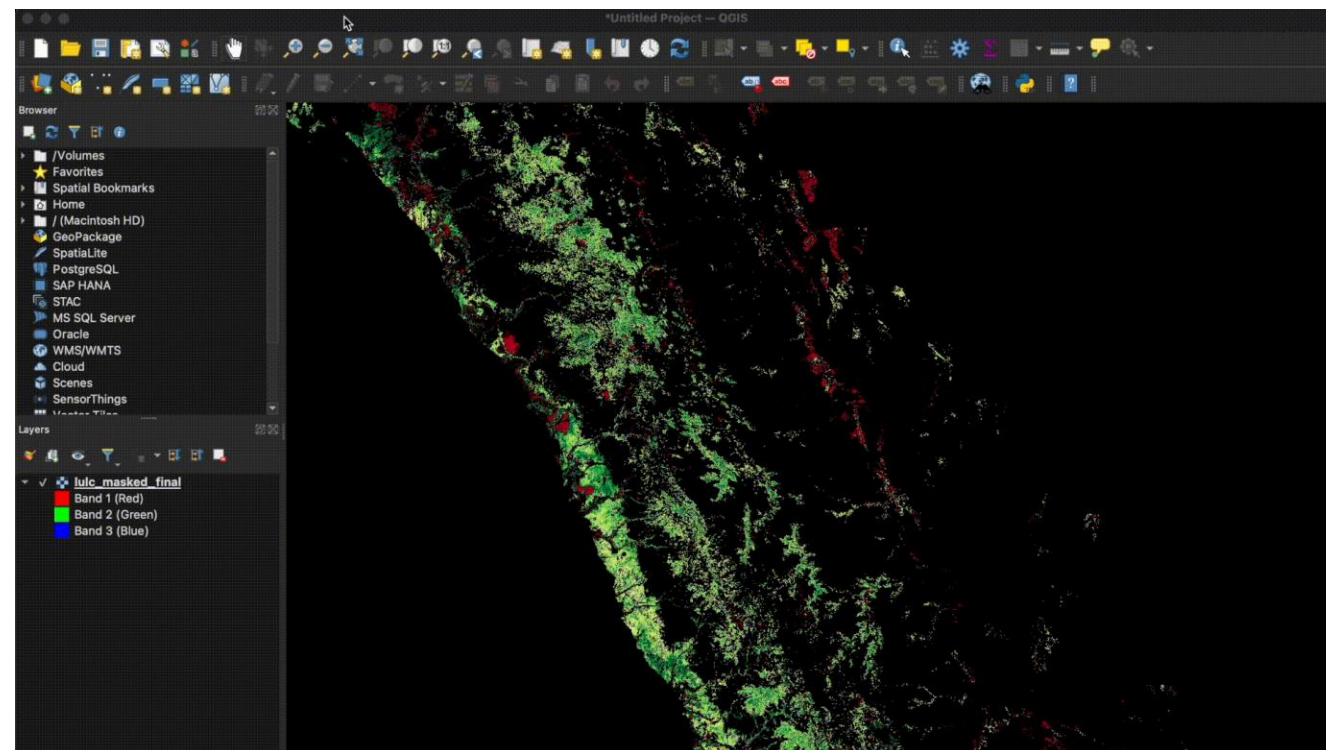
Use Land Cover Classification System (LCCS) to mask unwanted areas and then outline greening strip



Compute spatially averaged EVI time series within the greening strip and within the BWh, BWk, and BSk climate zones inside the study area and the greening strip



Process these time series like before but excluding the Upper Envelope Reconstruction. Also aggregate data to monthly means



*Fig 4: Example of outlining a region in QGIS*

# Methods – Calculating Correlations II

Obtain SST time series by averaging temperature over a region bounded from 6°S-30°S latitude and 70°W-80°W longitude. Remove seasonality and Whittaker smooth



Download atmospheric CO<sub>2</sub> trend data

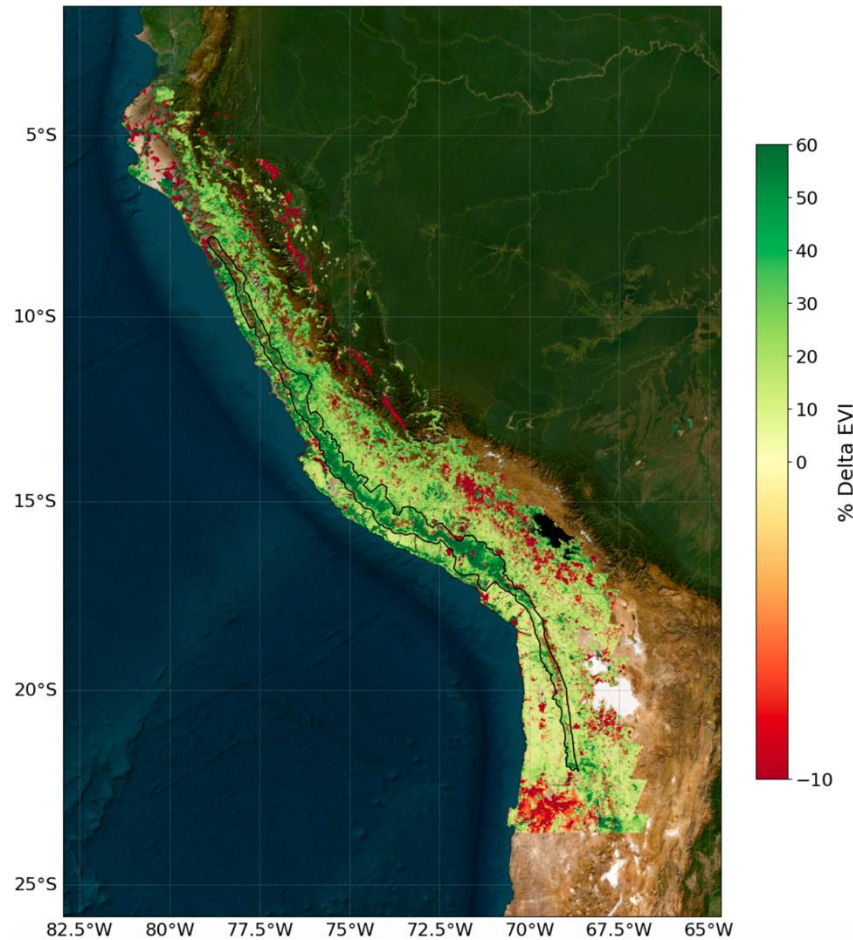


Compute monthly mean precipitation time series for the greening strip and for the BWh, BWk, and BSk climate zones inside the study area and the greening strip. Remove seasonality and Whittaker smooth



Compute lagged Spearman correlation between the spatially averaged EVI and climate driver time series

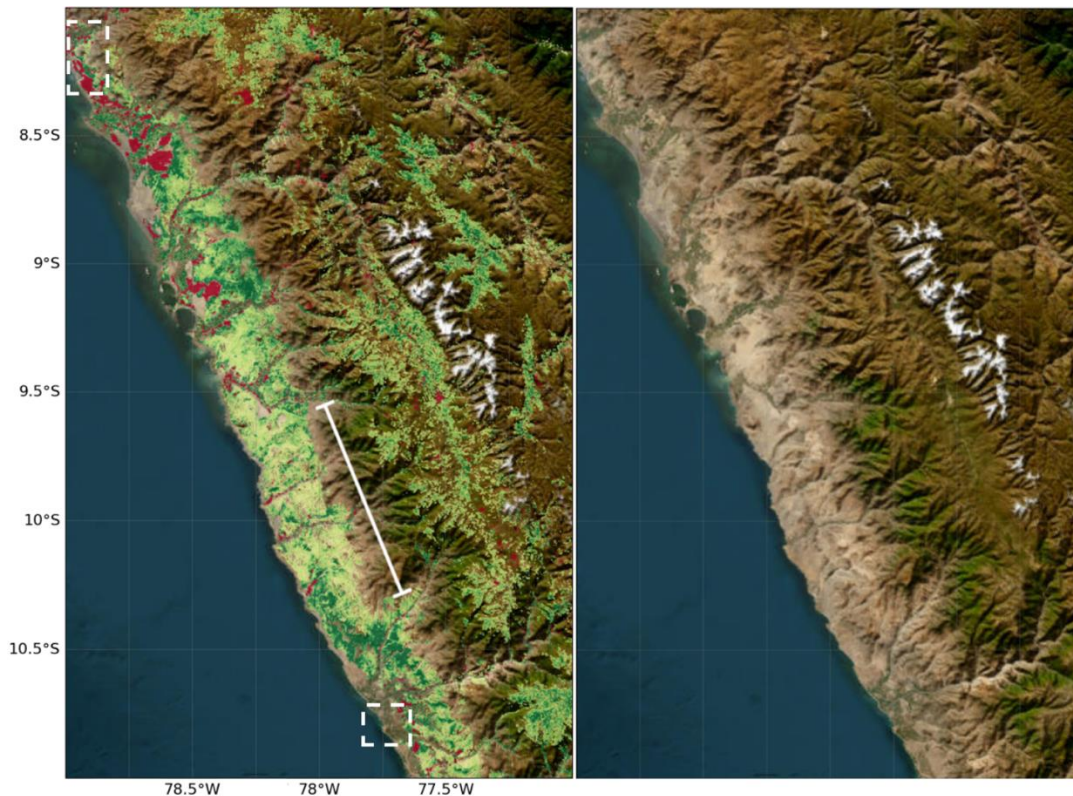
# Results – Peru & Northern Chile I



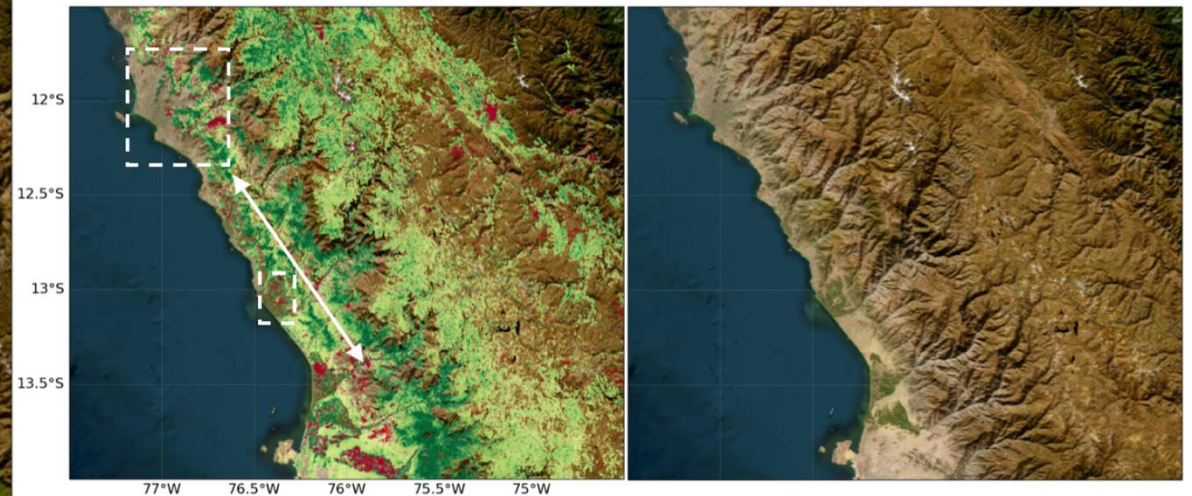
*Fig 5:  $\Delta_{EVI}$  heatmap overplotted on a satellite image of the study area. The greening strip is outlined in black*



## Results – Peru & Northern Chile II



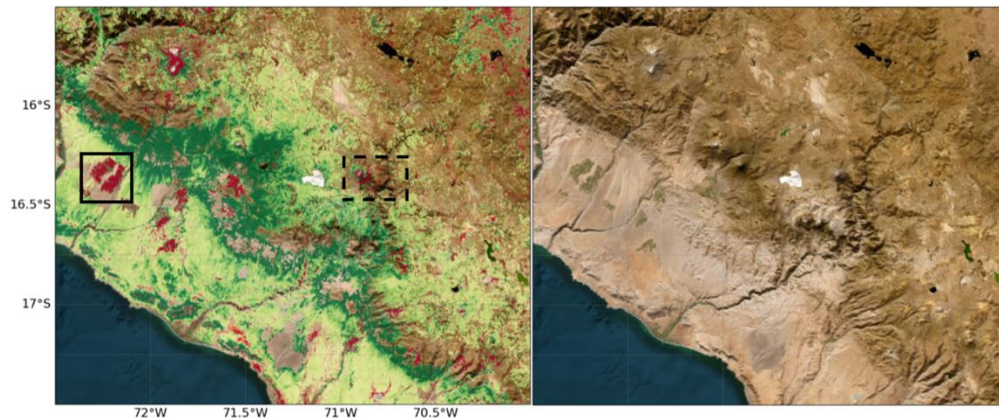
*Fig 6: A greening gap is observed from approx. 9.6°S-10.3°S. The top and bottom boxes are the cities of Trujillo and Barranca, respectively and were excluded from the analysis*



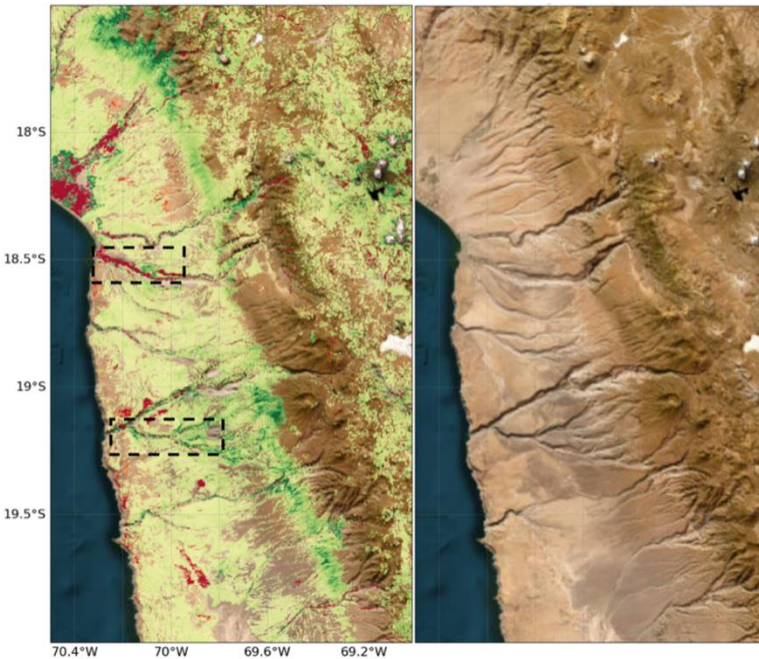
*Fig 7: The larger and smaller dashed boxes represent the city and province of Lima and Cañete, respectively. The double headed arrow separates greening occurring in the greening strip from coastline greening associated with coastal Lomas. Furthermore, can be seen that the greening increases in intensity southwards from Lima.*



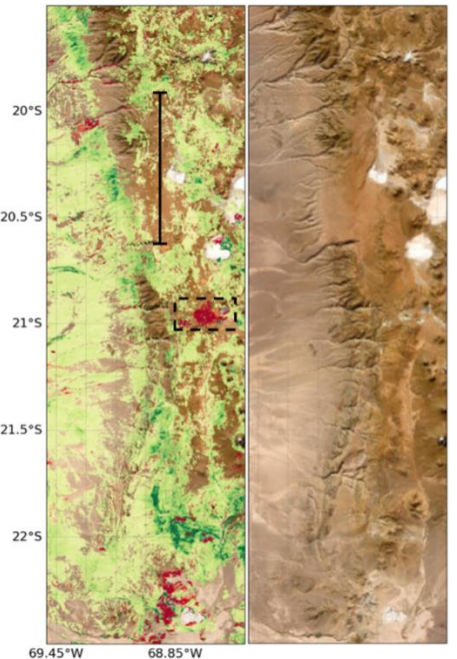
# Results – Peru & Northern Chile III



*Fig 8: The solid box shows the Majes irrigation project, and the dashed box represents the city of Arequipa. Both are examples of areas excluded in the analysis.*



*Fig 9: Coastal greening no longer observed. Dashed boxes illustrate roads/rivers and were excluded from the analysis*



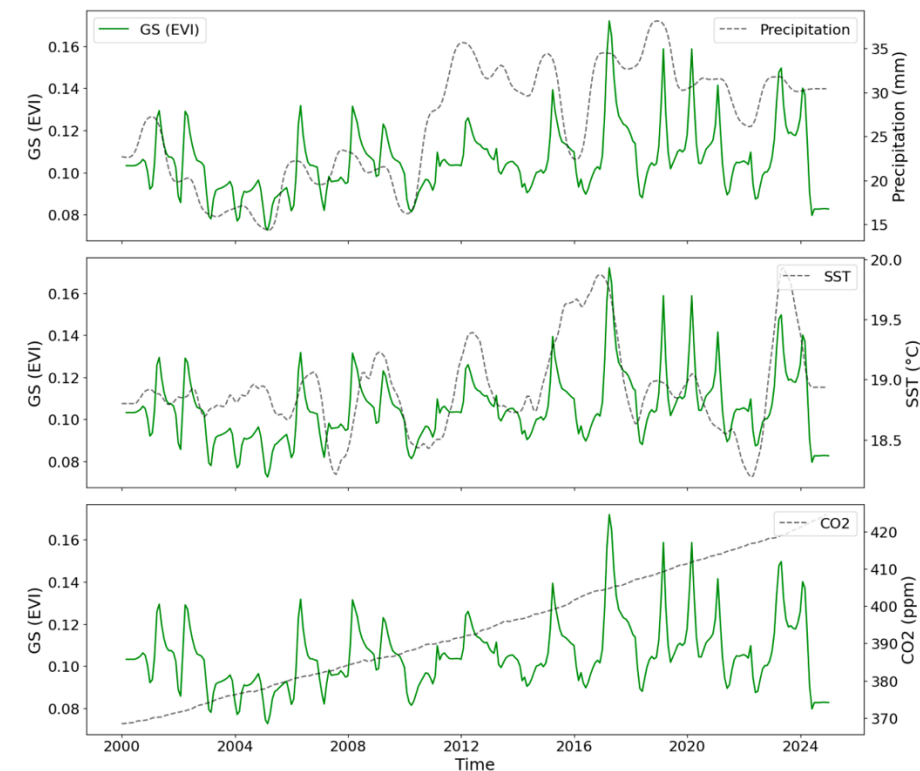
*Fig 10: Another greening gap observed between 19.9°S-20.6°S. Dashed box shows a mine/quarry*



# Results – Peru & Northern Chile IV

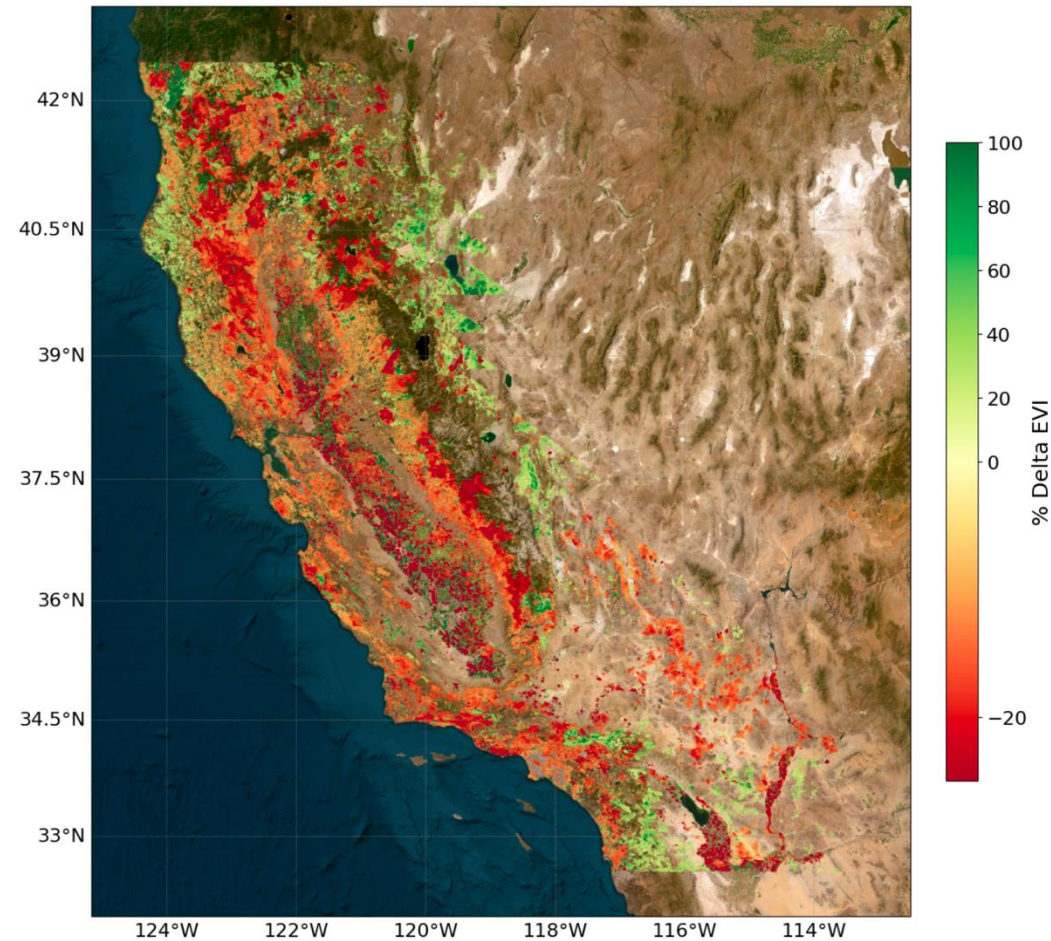
Region	Precipitation	SST	Global CO <sub>2</sub>
BWh	0.39	0.46	0.21
BWk	0.60	0.43	0.47
BSk	0.41	0.29	0.32
GS	0.51	0.43	0.36
GS_BWh	0.50	0.45	0.43
GS_BWk	0.55	0.46	0.36
GS_BSk	0.45	0.38	0.24

*Tab 1: Correlations between spatially averaged EVI time series for different K-G climate zones within both the full study area and the greening strip (GS), and climate drivers including precipitation, SST, and atmospheric CO<sub>2</sub> concentration.*



*Fig 11: Spatially averaged greening strip EVI time series with each climate driver's time series.*

## Extended Results – California, USA



*Fig 12:  $\Delta_{EVI}$  heatmap overplotted on a satellite image of California, USA.*

# Discussion – Peru & Northern Chile I

The same greening strip is observed

Original figure displays all pixels and the inset shows statistically significant pixels based on if  $|\Delta_{\text{EVI}}| > 15\%$

Figure obtained here displays statistically significant pixels based off Kendall's Tau and the p-value of the Mann-Kendall test

Note the Uyuni and Coipasa Salt Flats

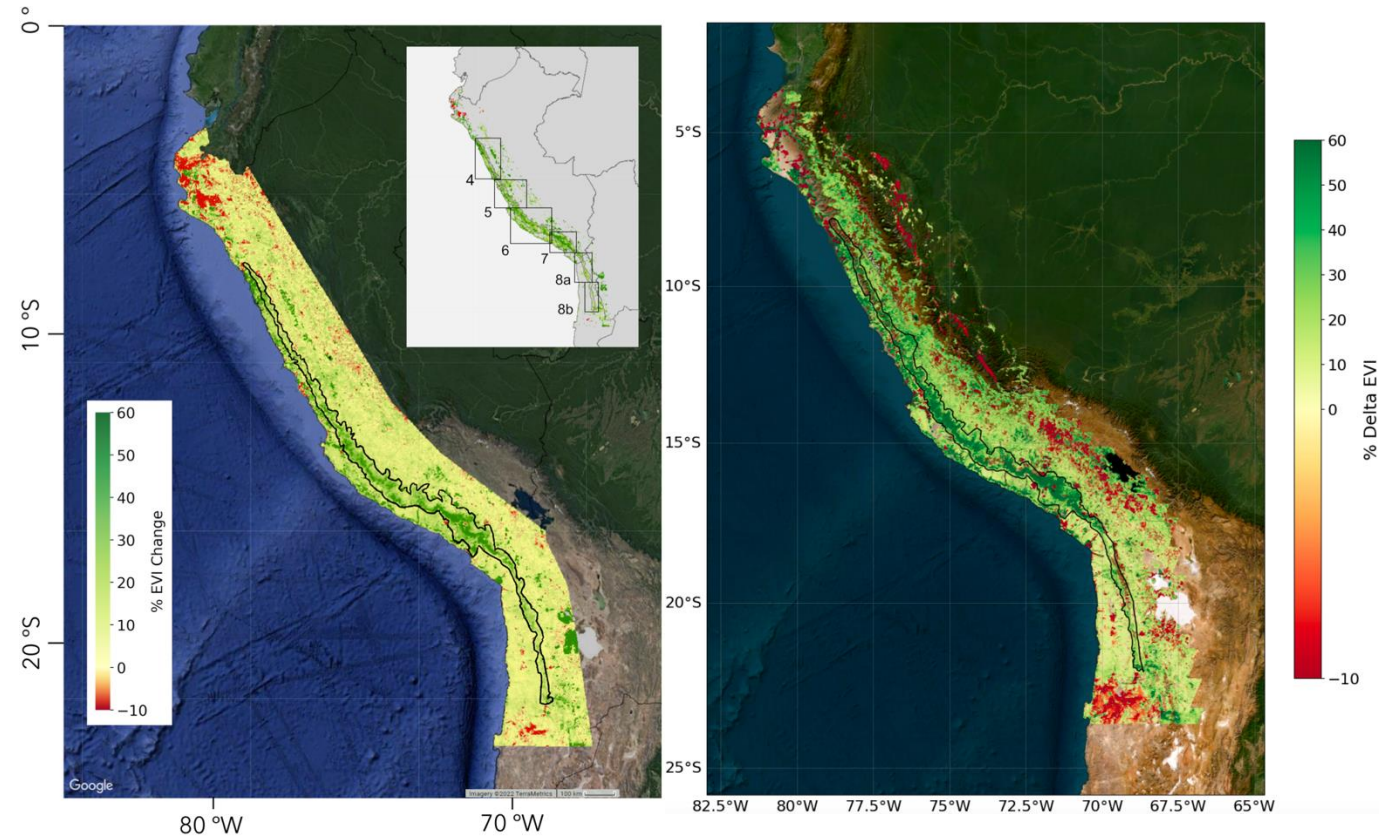


Fig 13: Left: Original work's figure [6]. Right: Figure obtained in this project



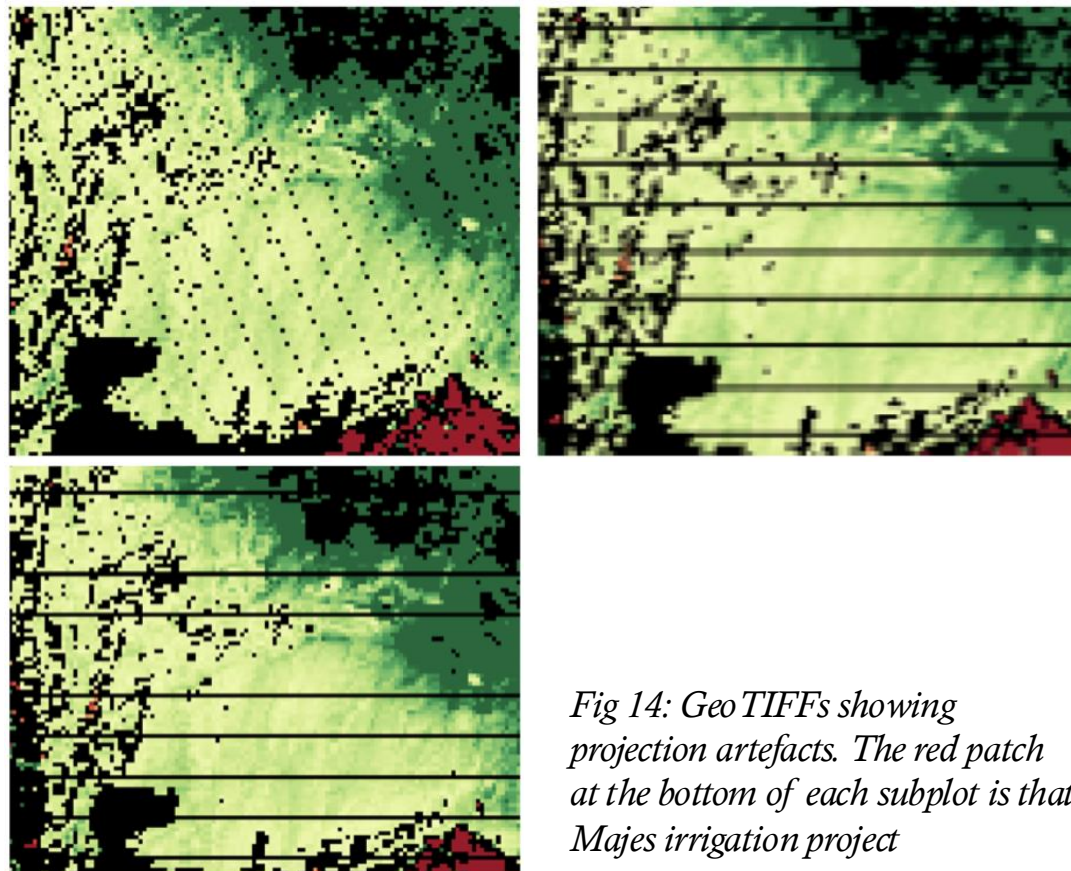
## Discussion – Peru & Northern Chile II

GeoTIFFs generated from the pipeline exhibited projection artefacts

Investigated by changing export projection and inspecting output

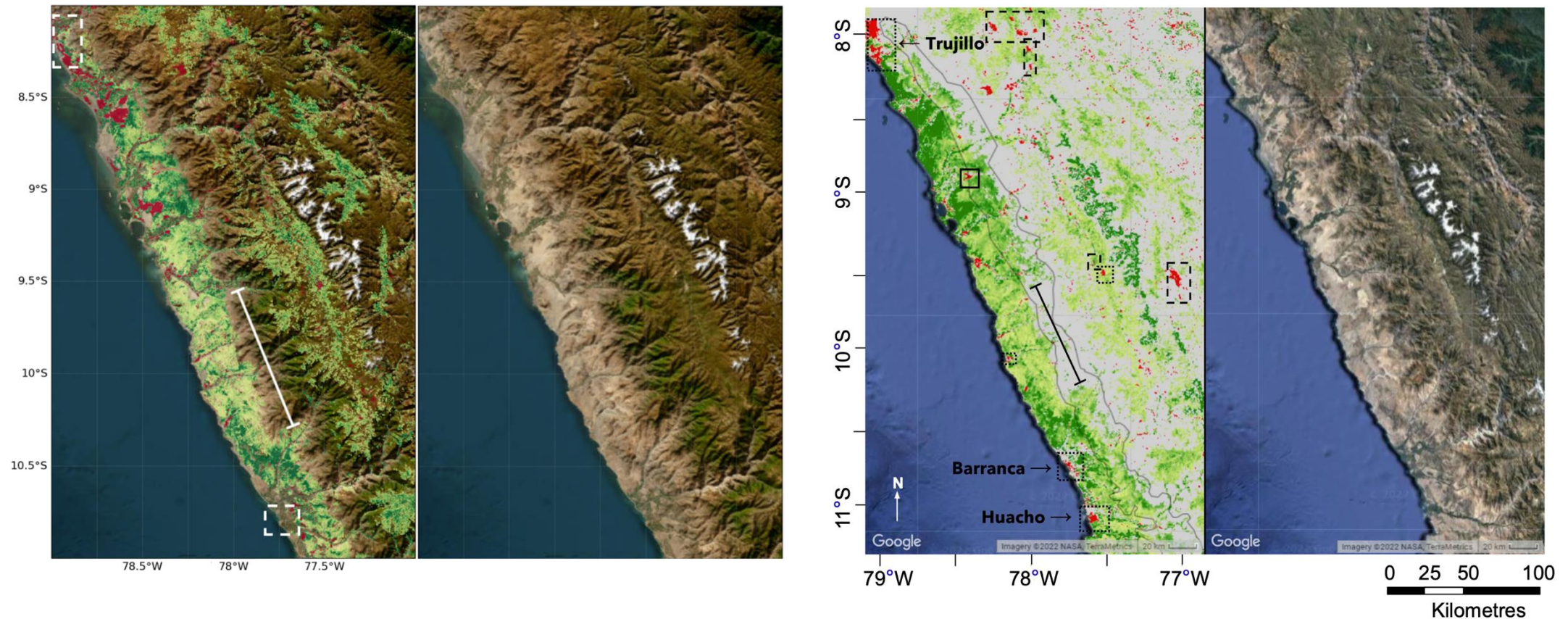
Not deemed to be a critical issue as no data is lost

Further investigate by using a different method to generate the GeoTIFFs



*Fig 14: GeoTIFFs showing projection artefacts. The red patch at the bottom of each subplot is that Majes irrigation project*

# Discussion – Peru & Northern Chile III



*Fig 15: Left: Project's figure. Right: Original work's figure [6]. We see a consistent observation of the greening gap. Note that in the original work, the glacier appears to be 'greening'*



# Discussion – Peru & Northern Chile IV

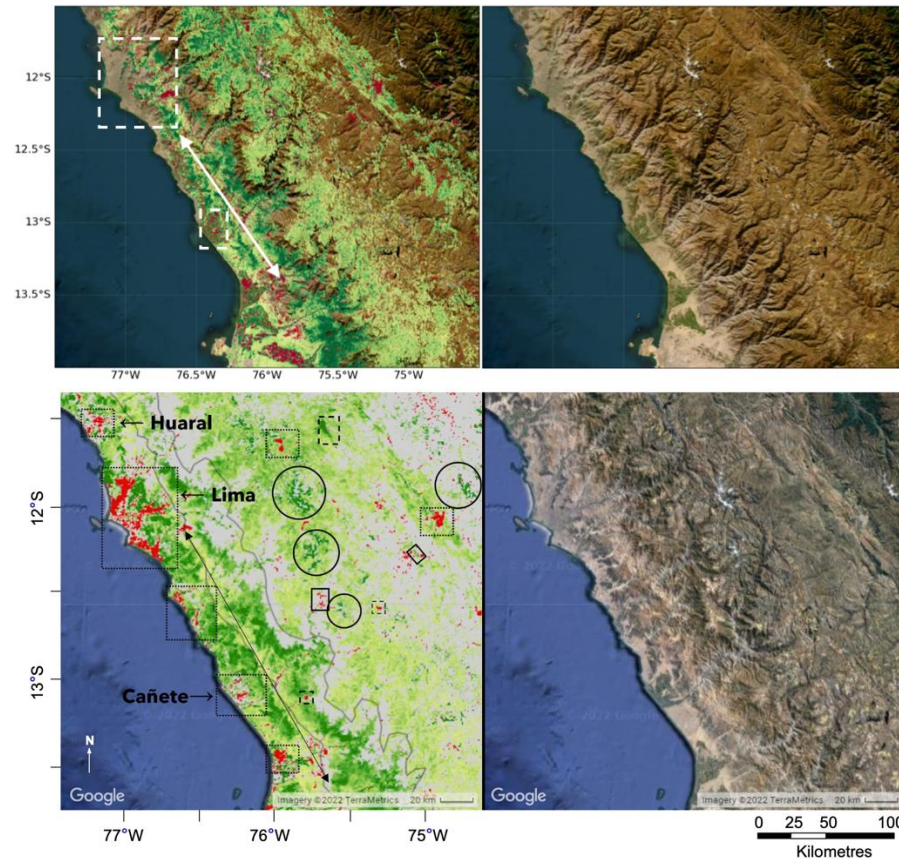


Fig 16: Top: Project's figure. Bottom: Original work's figure [6]. We see a consistent observation of coastal lomas and an increase in greening intensity

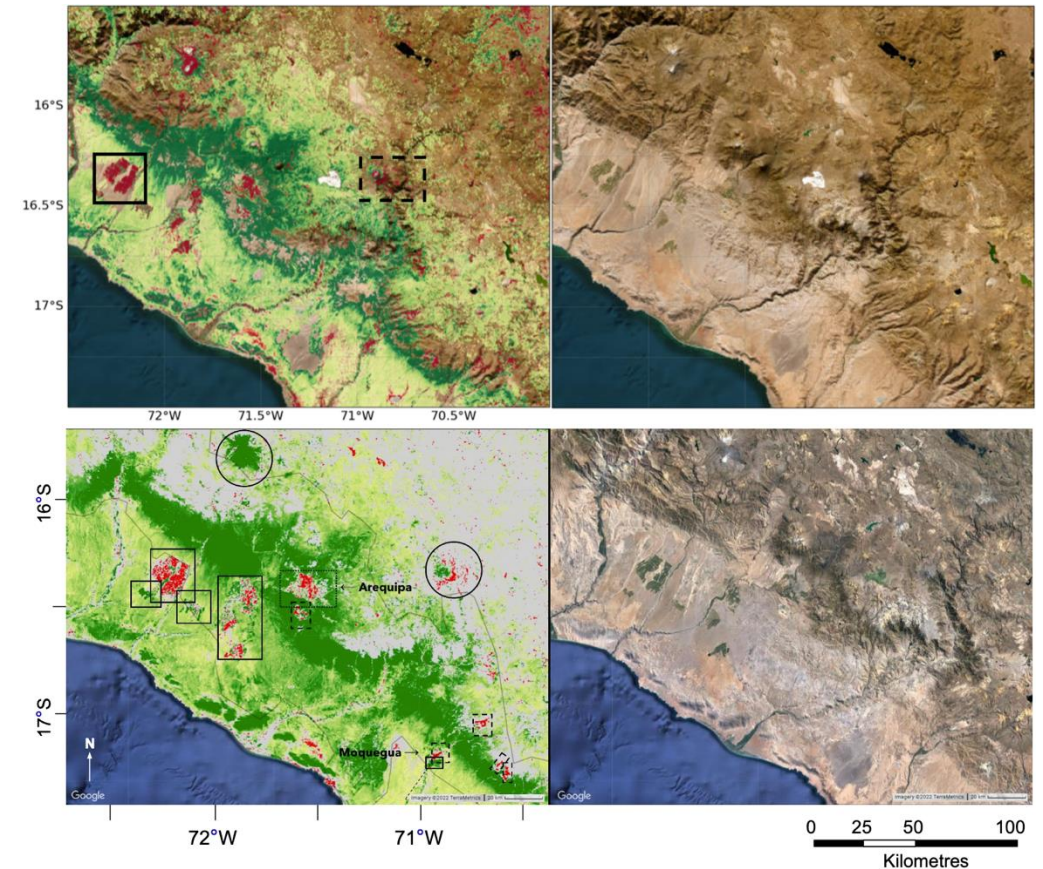
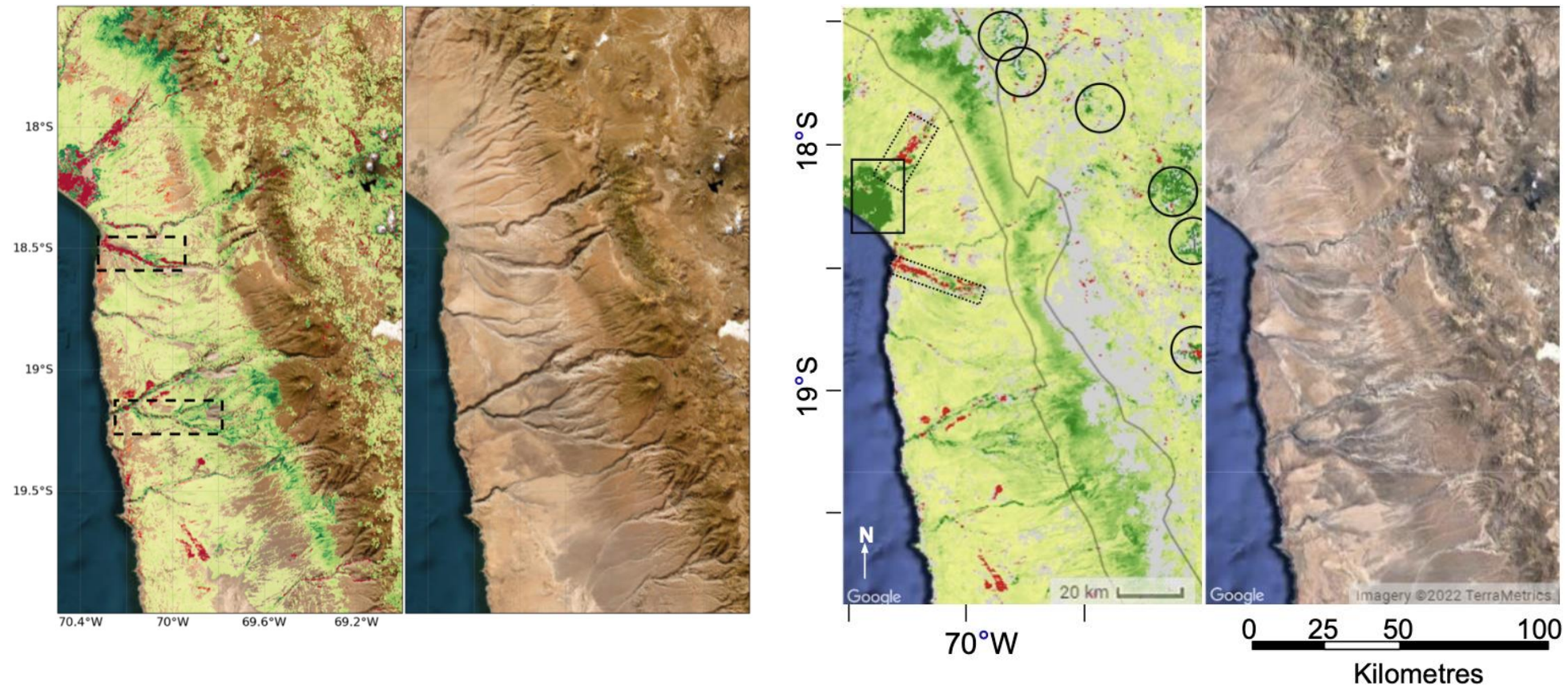


Fig 17: Top: Project's figure. Bottom: Original work's figure [6]. We see a consistent observation of Majes and strong greening next to it

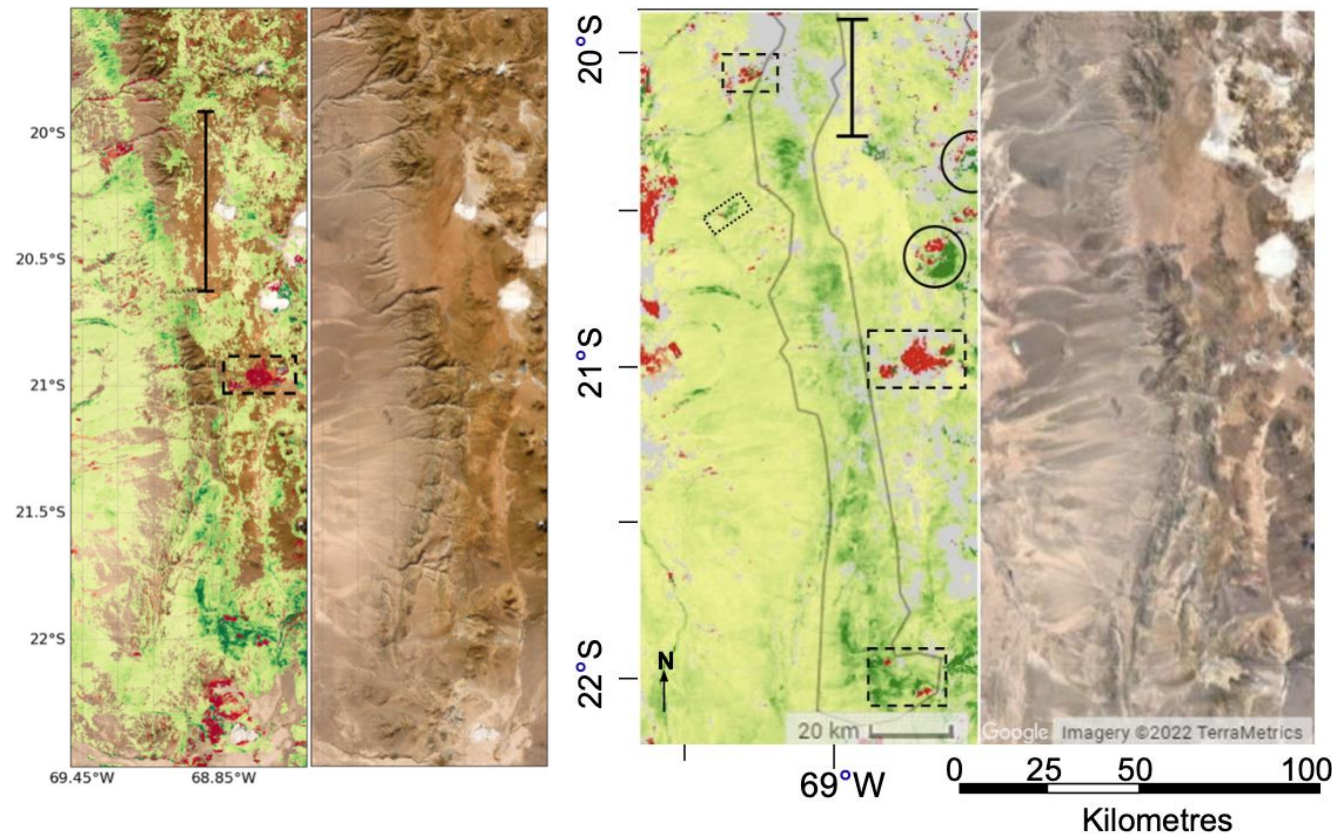


# Discussion – Peru & Northern Chile V



*Fig 18: Left: Project's figure. Right: Original work's figure [6]. We see a consistent observation of roads and rivers. Additionally, what used to be greening is now browning. Satellite images suggest this is agricultural land*

# Discussion – Peru & Northern Chile VI



*Fig 19: Left: Project's figure. Right: Original work's figure [6]. We see a consistent observation of the second greening gap where it has expanded by approx. 0.4 degrees southwards. Additionally, the mine/quarry is observed along with the end of the greening strip*



# Discussion – Peru & Northern Chile VII

This correlations determined in this project supports the original findings that:

- All correlations are positive
- EVI correlations with precipitation vary more outside the greening strip than within it
- EVI has lower correlation with SST and higher correlation with CO<sub>2</sub> outside the strip than within it

But there are some disagreements as:

- The BWh and GS\_BWh regions deviate from the expected trend
- The relative strengths of the correlations within each region differ

These discrepancies may be attributed to differences in the methodologies as:

- The original work doesn't fully describe the construction of EVI time series
- The processing of climate driver time series isn't fully described
- The lagged correlation implementation isn't fully described

# Discussion – Peru & Northern Chile VIII

Region	Precipitation	SST	Global CO <sub>2</sub>
BWh	0.39	0.46	0.21
BWk	0.60	0.43	0.47
BSk	0.41	0.29	0.32
<b>GS</b>	<b>0.51</b>	<b>0.43</b>	<b>0.36</b>
GS_BWh	0.50	0.45	0.43
GS_BWk	0.55	0.46	0.36
GS_BSk	0.45	0.38	0.24

Tab 2: Correlation table (same as Table 1)

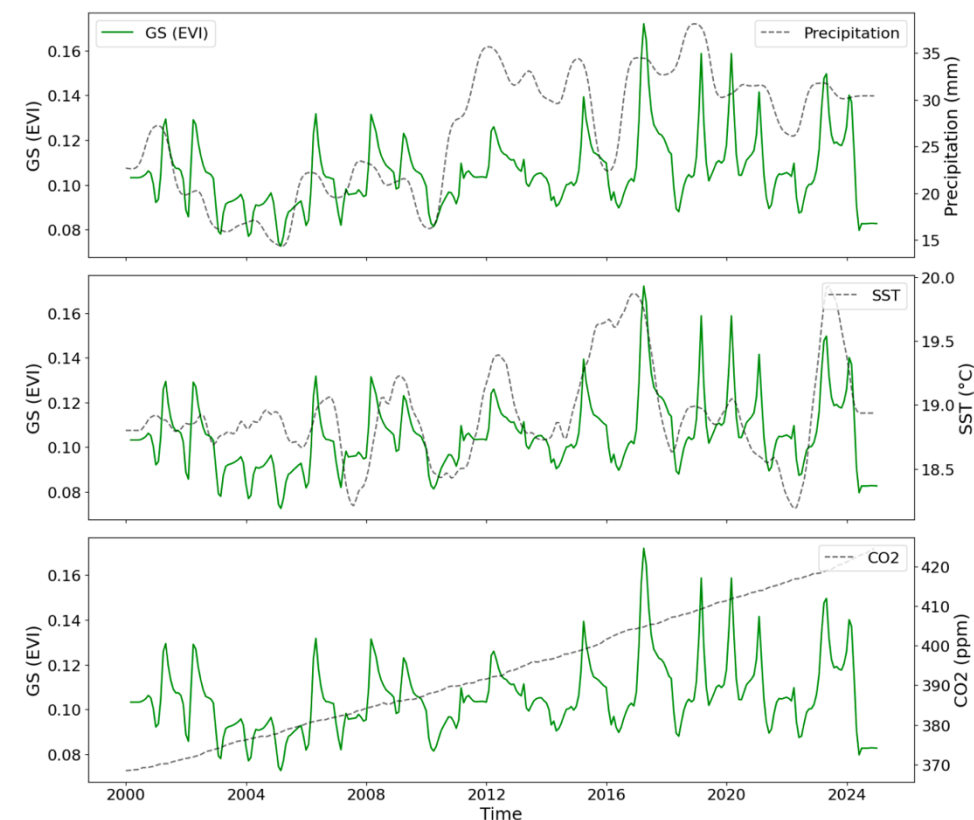


Fig 20: Spatially averaged greening strip EVI time series with each climate driver's time series.



# Discussion – California, USA

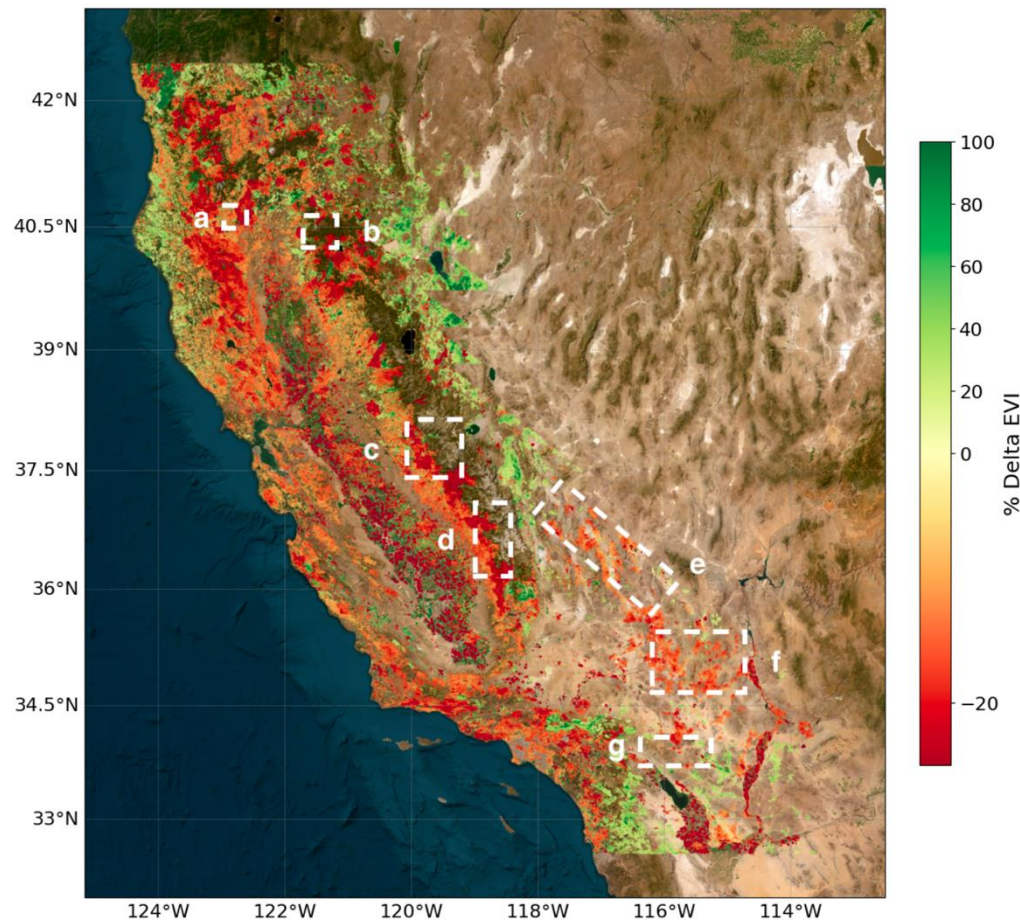


Fig 21:  $\Delta_{EVI}$  heatmap of California, USA with various national parks indicated. a) Whiskeytown-Shasta-Trinity National Recreation Area, b) Lassen Volcanic National Park, c) Yosemite National Park, d) Kings Canyon National Park & Sequoia National Park, e) Death Valley National Park, f) Mojave National Preserve, g) Joshua Tree National Park.

## Discussion – Directions for Further Studies

Apply the pipeline to study additional regions to generate a global  $\Delta_{\text{EVI}}$  map

- To facilitate rapid identification of greening/browning areas

Develop the pipeline into a Python package

- So it can be pip installable by members of the community

Integrate data from additional satellite platforms

- Such as Landsat/Sentinel-2 to supplement MODIS EVI data

Process multiple tiles in parallel using multiple threads

- Using libraries such as OpenMP in HPC environment

# Summary

Primary objective has been achieved

- Reproduced the statistically significant greening strip
- EVI correlations with climate drivers were analysed, highlighting both similarities and differences. Discrepancies were attributed to variations in methodology

Secondary objective also achieved

- Open-source pipeline in Python successfully developed
- Scalability and generality of the pipeline demonstrated through studying California, USA
- Directions for further studies proposed

For further details, please consult the GitLab repository, report, and executive summary

- Thank you for listening!