MONITORING VEGETATION TRENDS AS A RESULT OF CLIMATE CHANGE

USING SATELLITE MULTISPECTRAL DATA TO EXAMINE GREENING AND BROWNING TRENDS ON THE PACIFIC SLOPE OF PERU AND NORTHERN CHILE

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INTRODUCTION

The Pacific Slope of Peru and northern Chile is one of the most water scarce and climate vulnerable regions in South America [1]. It is home to significant levels of biological endemism [2–4] and major cities that depend on its limited water resources [5–8]. This region faces escalating threats from climate change, which could intensify existing pressures on both biodiversity [9] and resource availability [10], making environmental monitoring in the region increasingly urgent. One effective way to assess ecological impacts is by monitoring vegetation trends through remote sensing. Satellite instruments like MODIS (Moderate Resolution Imaging Spectroradiometer) provide time series data to evaluate vegetation health using indices such as the Enhanced Vegetation Index (EVI) [11, 12]. These indices offer valuable insights into vegetation responses to changing climate drivers. To contextualise vegetation trends, this study uses the Köppen-Geiger (K-G) climate classification system, which divides geographical areas into thirty distinct climate zones [13]. The study focuses on arid and semi-arid regions, including the hot desert (BWh), cold desert (BWk), and cold semi-arid steppe (BSk) zones, which remain relatively unmodified [14].

The primary objective of this project is to reproduce the findings of a recent study [14], which identified a statistically significant greening strip along the Pacific Slope of Peru and northern Chile. This includes replicating the vegetation trend through a time series analysis of MODIS EVI data from 2000 to 2024. The project also reproduces the study's correlation analysis between spatially averaged EVI and climate drivers such as atmospheric CO_2 concentration, Sea Surface Temperature (SST), and precipitation across different K-G climate zones. Replication studies such as this are a critical component of the scientific process, helping to verify and reinforce previous results. To demonstrate the broader applicability of the approach, the study was also extended to include the state of California, USA - a region which has experienced browning [15].

METHODS

This project followed a three step methodology: data acquisition, data processing, and correlation analysis.

Data Acquisition

The study area was manually defined in Google Earth Engine (GEE). Due to its large size and limited computational capacity, a tiling strategy was employed to divide the area into manageable segments for batch processing. For each tile, full EVI and Quality Assessment (QA) data were exported to Google Drive for all pixels spanning the 2000-2024 period.

Data Processing

Pixels with insufficient valid observations were excluded. For the remaining pixels, time series were processed by: (i) removing seasonality, and (ii) constructing an upper envelope of the time series. The Mann-Kendall test was used to estimate long term trends and filter out statistically insignificant pixels. The slope and intercept from the test was used to compute the relative change in EVI over the study period for each pixel.

Correlation Analysis

To focus on natural vegetation, urban, agricultural, and water areas were masked. The greening strip was manually traced and treated as a single region. For this region, and for each K-G climate zone within the greening strip and the broader study area, spatially averaged EVI time series were generated by averaging pixel level values at each time point. Climate driver time series included atmospheric CO_2 concentrations [16], SST averaged over the region 6°S-30°S latitude and 70°W-80°W longitude [17], and precipitation [18]. Monthly precipitation averages were computed for each region using a custom function. Finally, a function was implemented to compute the lagged Spearman correlation between each regional EVI time series and climate driver time series.

Key Findings

Peru & Northern Chile

The greening strip reported in the original work was successfully reproduced in this study, as shown in Figure 1.

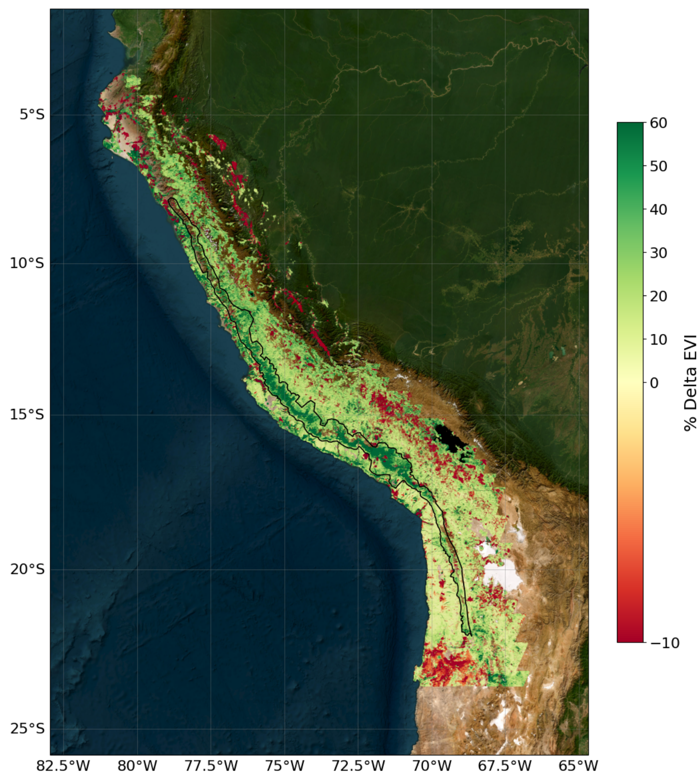

Figure 1: Δ_{EVI} heatmap illustrating the greening strip.

Notably, this version is considered an improvement over the original, as it visualises only statistically significant pixels. This removes spurious signals that could otherwise bias further analysis. Correlations between the EVI and climate driver time series are summarised in Table 1.

Region	Precipitation	SST	Global CO_2
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

Table 1: Correlations between EVI time series for different K-G climate zones within the full study area and the greening strip (GS), and climate drivers.

While some patterns were consistent with the original study, such as the relative correlations across regions, there were notable differences in the relative strength of correlations within individual regions. Despite these differences, the results presented here are internally consistent. The discrepancies between this work and the original study may stem from differences in the correlation methodology, due to certain processing steps not being fully described in the original work.

California, USA

The scalability and generality of the approach followed in this project was verified from applying the pipeline to California, USA, which generated Figure 2.

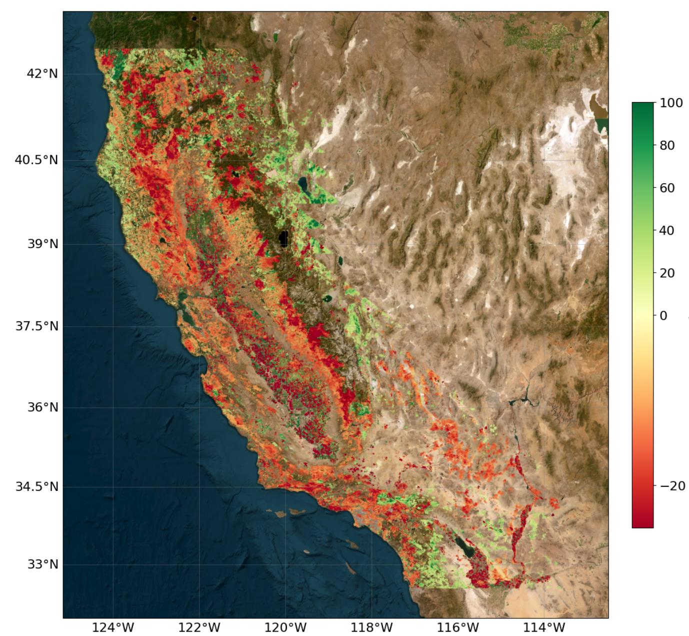

Figure 2: Δ_{EVI} heatmap of California, USA

Upon further investigation, it was found that many browning regions of California were associated with national parks, which is particularly concerning for nature conservation efforts and the preservation of biodiversity in the region.

Impacts of This Work

This project has successfully validated the observation of a statistically significant greening strip along the Pacific slope of Peru and northern Chile, thereby reinforcing the findings of the original study [14]. In addition, it led to the development of an open source, fully contained analysis pipeline in Python, leveraging the GEE API to acquire, process, and statistically analyse vegetation data. This pipeline lays the groundwork for future packaging into a Python library, making it easily installable via package managers such as `pip`, and accessible to the wider scientific community. This research contributes to an important field that supports data driven policymaking in areas such as ecosystem conservation, biodiversity protection, and sustainable natural resource management.

NEXT STEPS

An immediate direction for future research is to apply the analysis pipeline to additional regions, with the long term objective of generating a global Δ_{EVI} heatmap. Such a product would enable rapid identification of areas undergoing significant greening or browning trends. Further enhancements to the pipeline could include: (i) integrating data from additional satellite platforms to fill gaps in MODIS EVI coverage, thereby increasing pixel retention and reducing the patchiness currently seen in Δ_{EVI} heatmaps; and (ii) implementing multithreaded processing using libraries such as OpenMP within a high performance computing environment to enable parallel processing of multiple tiles and improve computational efficiency.

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