

PROYECTO CULTURAL, CIENTÍFICO Y COLECTIVO DE NACIÓN

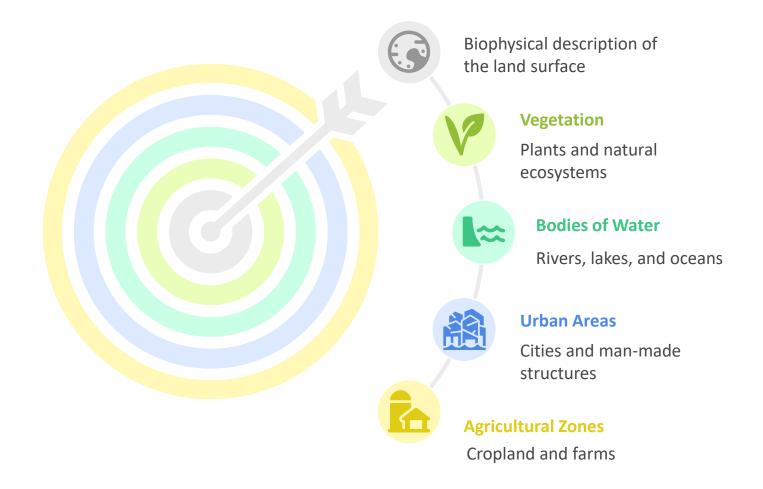
DE COLOMBIA

Daniela Rayo Álvarez

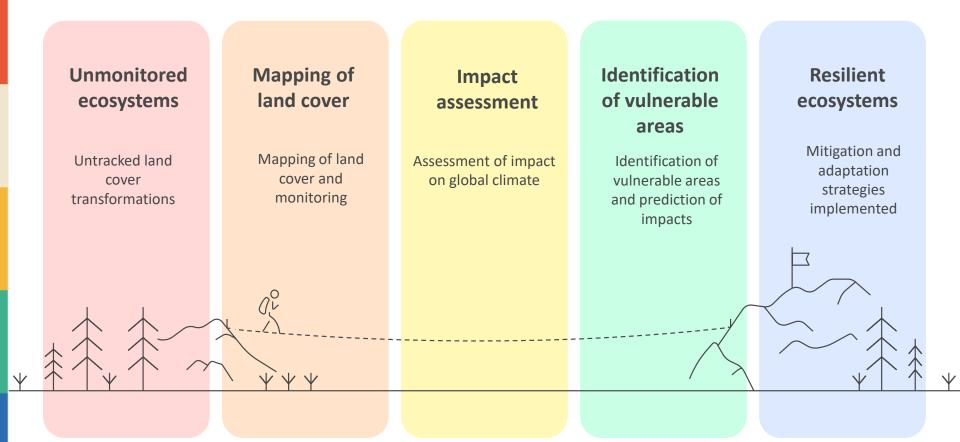
Facultad de Ciencias Agrarias

Universidad Nacional de Colombia

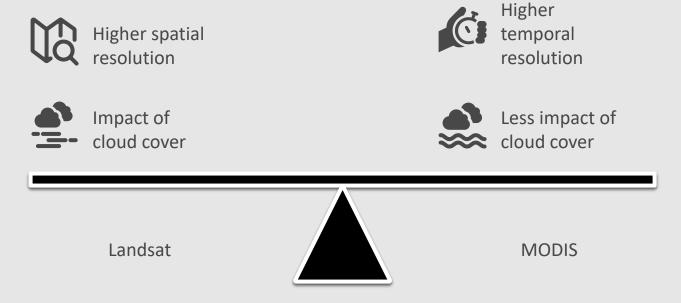
Land cover



Importance



Advances in change detection



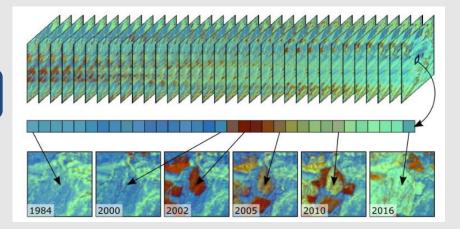
Algorithms for change detection

Algorithm	Description	Advantages	Limitations	Sources
CCDC	Harmonic model that uses all available Landsat images to detect changes continuously	High temporal and spatial accuracy, does not require thresholds.	High computational cost.	Zhu & Woodcock, 2014
CCDC-SMA	Combines CCDC with spectral analysis (SMA) to detect gradual and subtle degradation.	Detects sub-pixel changes and progressive degradation.	Requires high-quality spectral mixture data.	Chen et al., 2021
Lavad Tuavadu				
LandTrendr	Segments annual Landsat time series with straight lines to identify disturbances and recovery.	Ideal for abrupt changes; validated with field data.	It may not adequately capture very short-term events or anomalies if there is insufficient temporal data density.	Kennedy et al., 2010

LandTrendr

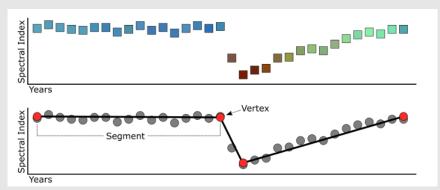
Input

Annual time series of an index.



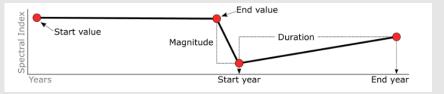
Process

Detects change vertices and allows interpolation.



Output

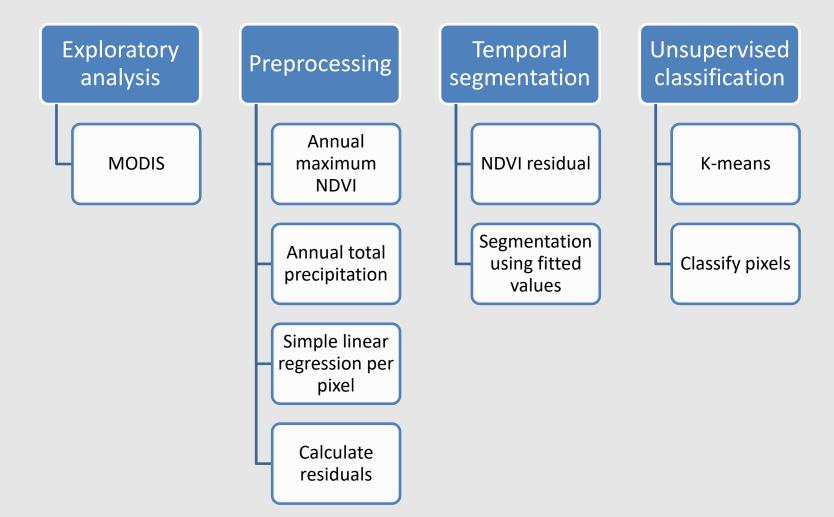
Simplified trajectory + temporal metrics.



More information



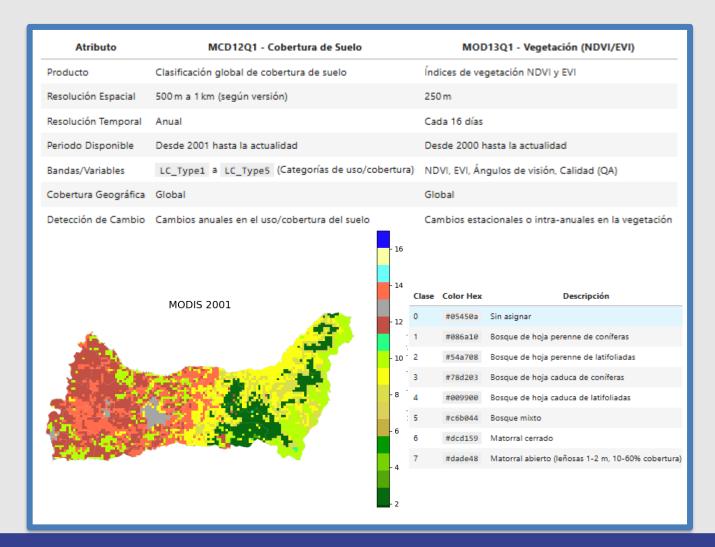
Methodology



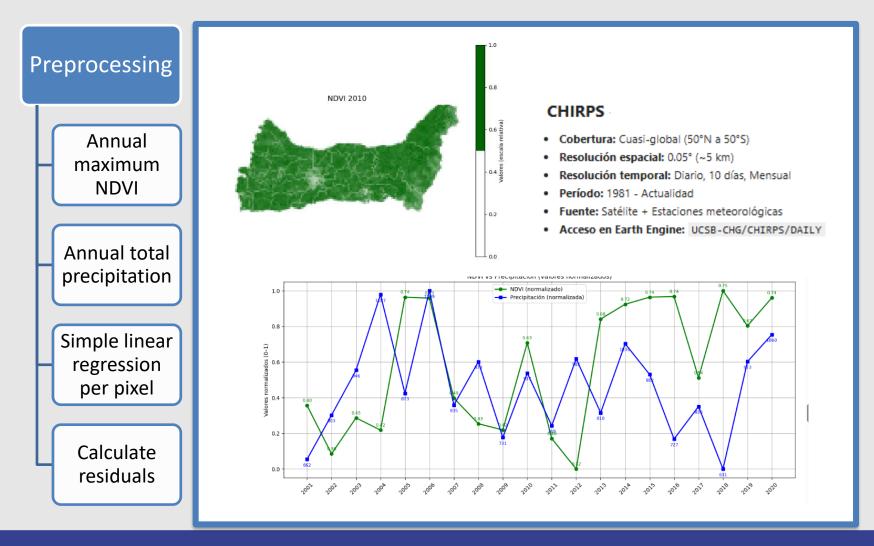
Methodology: exploratory analysis

Exploratory analysis

MODIS



Methodology: preprocessing

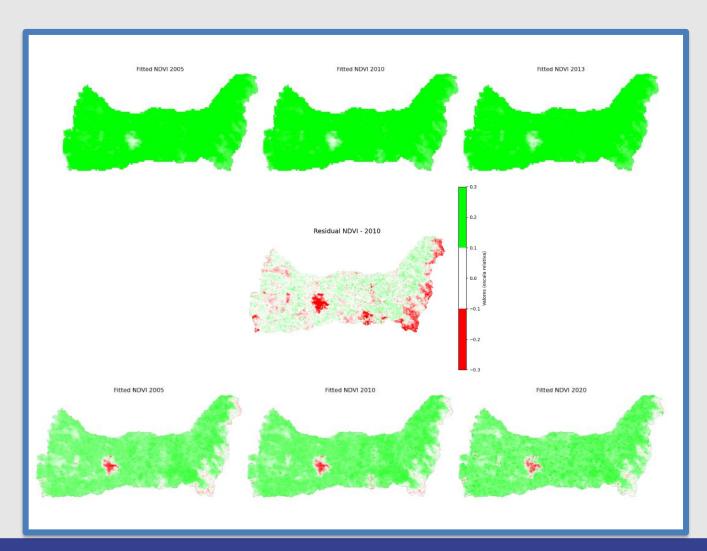


Methodology: temporal segmentation

Temporal segmentation

NDVI residual

Segmentation using fitted values

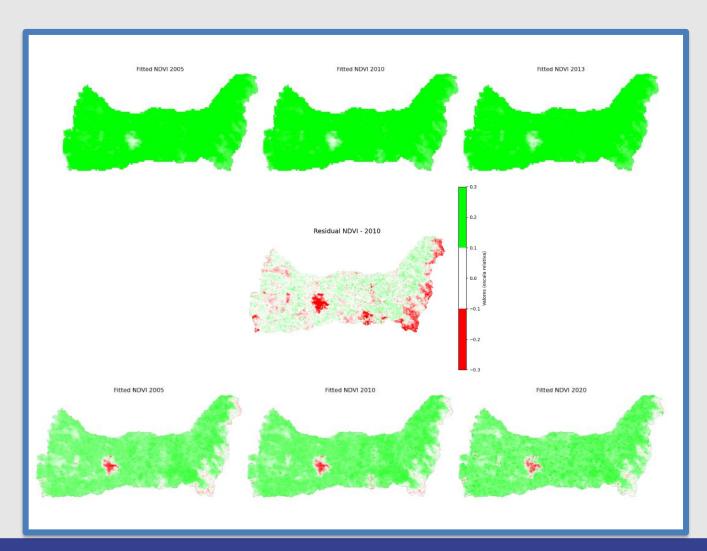


Methodology: temporal segmentation

Temporal segmentation

NDVI residual

Segmentation using fitted values



Methodology: temporal segmentation

Unsupervised classification

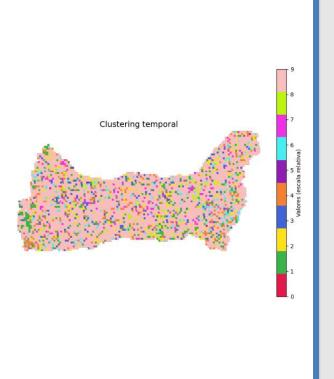
K-means

Classify pixels

- 1. Extraer vértices (vertex_stack):
 Se generan 20 bandas (una por año) que indican si hubo un cambio (vértice) en cada píxel entre 2001 y 2020 (valor 0 o 1).
- 2. Muestrear datos de entrenamiento:

Se extraen 5000 píxeles aleatorios con su historial de cambio (secuencia de 0s y 1s).

3. Entrenar K-means: Se agrupan los píxeles en 10 clusters según similitud en su historial de cambios temporales.



Conclusion

Temporal analysis of residual NDVI, combined with segmentation and unsupervised clustering, enables the detection of vegetation change patterns that are not visible with traditional methods. This methodology enhances the monitoring of dynamic ecosystems such as grasslands, allowing for more accurate environmental management.

References

Cardille, J. A., Crowley, M. A., Saah, D., & Clinton, N. E. (Eds.). (2023). *Cloud-based Remote Sensing with Google Earth Engine: Fundamentals and Applications*. Springer Nature.

Chen, S., Woodcock, C. E., Bullock, E. L., Arévalo, P., Torchinava, P., Peng, S., & Olofsson, P. (2021). Monitoring temperate forest degradation on Google Earth Engine using Landsat time series analysis. Remote Sensing of Environment, 265, 112648. https://doi.org/10.1016/j.rse.2021.112648

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Thanks



<u>GitHub</u>