**Congresos UEx. Actas de Congresos.** ISSN: 3101-7177,
vol. 2, 2026, XXI Congreso de la Asociación Española de Teledetección
DOI: https://doi.org/10.17398/3101-7177.2.279



# Does GEOBIA enhance vegetation classification performance in heterogeneous and dynamic landscapes?

**Pfitzer-López, Daniel** [1] **Roces-Díaz, José V.** [1] **Fernández-Guisuraga, José M.** [2] **García-Candanedo, Lucía** [1] **Suárez-Seoane, Susana** [1]

[1] Instituto Mixto de Investigación en Biodiversidad (IMIB)

[2] Departamento de Biodiversidad y Gestión Ambiental, Facultad de Ciencias Biológicas y Ambientales, Universidad de León, León, España.

**ORCID:** Pfitzer-López 0009-0009-4167-4398 Roces-Díaz 0000-0003-2569-8049 Fernández-Guisuraga 0000-0002-6065-3981 García-Candanedo 0009-0005-5272-9033 Suárez-Seoane 0000-0001-7656-4214

**Correspondencia:** pfitzerdaniel@uniovi.es rocesjose@uniovi.es jofeg@unileon.es garciacanlucia@uniovi.es s.seoane@uniovi.es

## ABSTRACT

Mapping vegetation types in heterogeneous and dynamic landscapes using long satellite image time series remains challenging due to uncertainties associated with spectral similarity among classes, phenological variability, and sensor differences. This study evaluates different classification approaches using Landsat imagery (1984-2024) processed in Google Earth Engine to map landscape dynamics in Asturias (NW Spain), a region characterized by steep terrain and high environmental heterogeneity. Image preprocessing included cloud masking, topographic correction, and bi-seasonal compositing to capture phenological differences. Four analysis years were selected (1984, 1998, 2008, and 2023), and 21 predictor variables were compiled, including 12 spectral bands, six texture metrics, and three biophysical traits. To perform the classifications, temporally invariant training polygons were defined using a change detection algorithm, allowing their reuse across all analysis years. Two Random Forest modelling approaches were implemented, pixel-based and object-based, exploring the performance of the three predictor groups both independently and additively. Objects were defined using object-based image analysis techniques (GEOBIA), grouping spectrally and spatially homogeneous pixels. Pixel-based models using spectral bands showed the highest performance (OA ≈ 0.88) and low interannual variability, indicating that invariant polygons enable the use of a single training dataset without loss of performance and with reduced data preparation effort. Although GEOBIA did not improve overall accuracy, it did enhance the classification of fast-growing forest plantations (FSCORE +0.13), likely due to their monospecific composition and well-defined spatial boundaries. We conclude that GEOBIA approaches may be more suitable for clearly delineated vegetation types, whereas pixel-based classifications may be more appropriate for monitoring heterogeneous landscapes.

**Keywords:** *Landsat, Continuous Change Detection, Superpixels Segmentation*

**Fecha de recepción:** 21 febrero 2026 · **Fecha de aceptación:** 21 febrero 2026

 

# Does GEOBIA enhance vegetation classification performance in heterogeneous and dynamic landscapes?

**Pfitzer-López, Daniel [(1)], Roces-Díaz, José V. [(1)], Fernández-Guisuraga, José M. [(2)], García-Candanedo, Lucía [(1)], Suárez-Seoane, Susana [(1)]**

[(1)] Instituto Mixto de Investigación en Biodiversidad (IMIB, Universidad de Oviedo – CSIC – Principado de Asturias) y Departamento de Biología de Organismos y Sistemas (Universidad de Oviedo), Oviedo España.

0009-0009-4167-4398, pfitzerdaniel@uniovi.es ; 0000-0003-2569-8049, rocesjose@uniovi.es

0009-0005-5272-9033, garciacanlucia@uniovi.es ; 0000-0001-7656-4214, s.seoane@uniovi.es

[(3)] Departamento de Biodiversidad y Gestión Ambiental, Facultad de Ciencias Biológicas y Ambientales, Universidad de León, España.

0000-0002-6065-3981, jofeg@unileon.es.

**Abstract**: Mapping vegetation types in heterogeneous and dynamic landscapes using long satellite image time series remains challenging due to uncertainties associated with spectral similarity among classes, phenological variability, and sensor differences. This study evaluates different classification approaches using Landsat imagery (1984-2024) processed in Google Earth Engine to map landscape dynamics in Asturias (NW Spain), a region characterized by steep terrain and high environmental heterogeneity. Image preprocessing included cloud masking, topographic correction, and bi-seasonal compositing to capture phenological differences. Four analysis years were selected (1984, 1998, 2008, and 2023), and 21 predictor variables were compiled, including 12 spectral bands, six texture metrics, and three biophysical traits. To perform the classifications, temporally invariant training polygons were defined using a change detection algorithm, allowing their reuse across all analysis years. Two Random Forest modelling approaches were implemented, pixel-based and object-based, exploring the performance of the three predictor groups both independently and additively. Objects were defined using object-based image analysis techniques (GEOBIA), grouping spectrally and spatially homogeneous pixels. Pixel-based models using spectral bands showed the highest performance (OA ≈ 0.88) and low interannual variability, indicating that invariant polygons enable the use of a single training dataset without loss of performance and with reduced data preparation effort. Although GEOBIA did not improve overall accuracy, it did enhance the classification of fast-growing forest plantations (FSCORE +0.13), likely due to their monospecific composition and well-defined spatial boundaries. We conclude that GEOBIA approaches may be more suitable for clearly delineated vegetation types, whereas pixel-based classifications may be more appropriate for monitoring heterogeneous landscapes.

**Keywords**: Landsat, Continuous Change Detection, Superpixels Segmentation

## *¿Mejora el enfoque GEOBIA el rendimiento de la clasificación de la vegetación en paisajes heterogéneos y dinámicos?*

***Resumen:*** *El seguimiento de los tipos de vegetación en paisajes heterogéneos y dinámicos mediante series temporales largas de imágenes de satélite constituye un reto debido a la incertidumbre asociada a la similitud espectral entre clases, los cambios fenológicos o las diferencias entre sensores. En este estudio se evalúan distintos enfoques de clasificación utilizando imágenes Landsat (1984-2024) procesadas en Google Earth Engine para cartografiar la dinámica del paisaje en Asturias, una región abrupta con elevada heterogeneidad ambiental. El preprocesamiento incluyó máscaras de nubes, corrección topográfica y composiciones biestacionales para capturar diferencias fenológicas. Se seleccionaron cuatro años de análisis (1984, 1998, 2008 y 2023) y 21 variables predictoras: 12 bandas espectrales, seis métricas texturales y tres rasgos biofísicos. Para llevar a cabo las clasificaciones, se definieron, mediante un algoritmo de detección de cambio, polígonos de entrenamiento temporalmente invariantes y, por tanto, reutilizables para todos los años de análisis. Se establecieron dos aproximaciones de modelado basadas en Random Forest: píxel vs. objetos, explorando el rendimiento de los tres grupos de predictores de manera independiente y aditiva. Los objetos se definieron mediante* *técnicas de segmentación basadas en objetos (GEOBIA) que agruparon píxeles espectral y espacialmente homogéneos. Los modelos a nivel píxel basados en bandas espectrales mostraron un mayor rendimiento (OA $\approx$ 0.88) y una baja variabilidad interanual, indicando que los polígonos invariantes permiten aplicar un único conjunto de entrenamiento sin pérdida de rendimiento y con menor esfuerzo en la preparación de datos. Aunque GEOBIA no mejoró la precisión global, sí mejoró la clasificación de plantaciones forestales de crecimiento rápido (FSCORE +0.13), probablemente por su composición monoespecífica y límites espaciales bien definidos. Se concluye que los enfoques basados en objetos podrían ser más adecuados para clasificar tipos de vegetación claramente delimitados, mientras que las clasificaciones a nivel de píxel podrían resultar más pertinentes en contextos heterogéneos.*

***Palabras clave:*** *Landsat, Detección continua de cambios, Segmentación Superpixel*

## 1. INTRODUCTION

Mapping broad vegetation types over long time periods through satellite remote sensing remains challenging, particularly in heterogeneous and changing landscapes, where spectral overlaps among vegetation types and phenological variability introduces classification uncertainty. Pixel-based classifications that rely mainly on spectral information often exhibit limited temporal transferability (Verhulst *et al*., 2024), whereas Geographic Object-Based Image Analysis (GEOBIA) approaches explicitly incorporate spatial context and may improve classification consistency. Accordingly, this study aims to develop a standardized framework for long-term landscape monitoring and to systematically compare the performance of pixel-based vs. GEOBIA classifications across four decades of Landsat observations.

## 2. MATERIALS AND METHODS

### 2.1. Study area

The Principality of Asturias is located in northwestern Spain and covers 10,604 km². This region is characterized by a humid oceanic climate, with mean annual precipitation exceeding 1,000 mm and mean annual temperatures ranging from 12 to 14 °C. Its rugged topography (ranging from sea level to ~2,650 m.a.s.l.) supports heterogeneous landscapes composed of fine-grained mosaics of settlements, agricultural lands, tree plantations mainly concentrated in coastal lowlands and semi-natural woody vegetation shifted to inland areas. The latter is dominated by temperate broad-leaved forests and heathlands. Ongoing rural depopulation has driven contrasting land-use trajectories, including agricultural intensification and eucalyptus plantation expansion, alongside passive rewilding (Pfitzer-López *et al*., 2026), reshaping the landscape over recent decades.

### 2.2. Landsat data preprocessing

Landsat Collection 2 Tier 1 Surface Reflectance products (Landsat 5 TM and Landsat 8 OLI) were retrieved from Google Earth Engine (GEE). Images with cloud cover below 25% were selected, and clouds and shadows were masked using the Landsat pixel quality assessment band. Topographic illumination effects were corrected using the Sun-Canopy-Sensor C algorithm. Median composites were generated using a three-year temporal window centered on each target year (i.e.; 1984, 1998, 2008 and 2023) to ensure spatial completeness, with a bi-seasonal (summer-winter) design adopted to exploit vegetation spectro-phenological differences (López Trullén *et al*., 2022) and to improve discrimination between eucalyptus plantations and native broad-leaved forests (Martin-Gallego *et al*., 2024). The selected target years correspond to intermediate points within the study period and were chosen based on model performance, prioritizing classification accuracy according to validation metrics rather than enforcing strict temporal equidistance.

### 2.3. Predictors

A total of 21 predictor variables were derived for each analysis year, including the six Landsat surface reflectance bands (blue, green, red, NIR, SWIR1 and SWIR2) acquired for both summer and winter (12 spectral predictors), six texture metrics and three biophysical traits: fractional vegetation cover (FCOVER), leaf water content (Cw), and chlorophyll content (Cab).

Texture metrics were computed as the standard deviation within a 5 x 5 pixel moving window to capture spatial variability associated with landscape structure not fully represented by spectral information alone. The window size was selected after comparative testing, as it provided the greatest improvement in validation performance.

Biophysical traits were retrieved through radiative transfer model inversion using PROSAIL. Ranges input parameters were defined based on field knowledge, scientific literature on similar simulations in the region (e.g. Fernández-Guisuraga *et al*., 2024), and Landsat images metadata. These parameters were used to generate a synthetic dataset of spectral simulations, which were subsequently convolved with the spectral response functions of Landsat 5 TM and Landsat 8 OLI. The resulting simulated database was then used to train Random Forest models (500 trees) to retrieve fractional FCOVER, Cw, and Cab.

### 2.4. GEOBIA segmentation

The full predictor set was used as input to the SNIC (Simple Non-Iterative Clustering) spatial segmentation algorithm (Achanta & Susstrunk, 2017), implemented in GEE. SNIC generates homogeneous superpixels objects by jointly considering spectral similarity and spatial proximity, which reduces within-object variability and pixel-level noise.

### 2.5. Unchanged training polygons

A single set of 697 training polygons was used across all analysis years to support consistent vegetation types classification over time. This strategy avoids the need to delineate year-specific training data, improving operational efficiency. Unchanged vegetation types areas were first identified at the pixel level using the Continuous Change Detection (CCD) algorithm (Arévalo *et al*., 2020; Zhu & Woodcock, 2014) and subsequently validated through visual interpretation of historical PNOA orthophotographs (pnoa.ign.es). Training polygons were manually delineated in homogeneous core areas for five vegetation types classes: sparsely vegetated areas and pasturelands; herbaceous and woody agricultural lands; heathlands and shrublands; fast growing tree plantations (including conifers and eucalyptus); and native forests. Moreover, field surveys were conducted to validate a subset of polygons, and a fixed, temporally static mask was applied for water bodies and urban areas.

## 2.6. Classification and validation

Classification of vegetation types was conducted using Random Forest (500 trees) at both pixel and GEOBIA levels. Predictor contributions were assessed by comparing models built with individual predictor groups and under an additive framework. Temporally invariant training polygons were split into training (70%) and validation (30%) independent subsets using class-stratified sampling. Model performance was assessed using confusion matrices, from which Overall Accuracy (OA) and F-scores were derived for each analysis year. Additionally, SNIC parameters were iteratively tuned by testing multiple values until classification performance was maximized

# 3. RESULTS AND DISCUSSION

Pixel-level and GEOBIA classifications (Figure 1) showed very similar overall accuracy across all predictor groups for the analyzed years (1984, 1998, 2008, and 2024; Table 1) in both the individual predictor and the additive models, with pixel-based models performing slightly better. Within the pixel-level models, spectral reflectance alone provided the highest performance (0.88 ± 0.03), suggesting limited added value from non-spectral predictors. The inclusion of texture metrics resulted in only marginal improvements, with no additional gains observed after incorporating biophysical variables. The low standard deviation of overall accuracy across years indicates that using unchanged training polygons did not lead to performance degradation in earlier periods. This supports the feasibility of applying a single training dataset across multi-decadal satellite time series, reducing the need for year-specific training data and simplifying the modelling workflow.

**Table 1.** Overall accuracy of pixel-based and GEOBIA classifications across predictor groups (spectral, texture, biophysical) for individual predictor models and additive models.

| Predictor group | Classification level | |
|---|---|---|
| | Pixel (average ± SD) | Geobia (average ± SD) |
| L8 SR Bands | 0.88 ± 0.03 | 0.86 ± 0.05 |
| Texture | 0.63 ± 0.05 | 0.64 ± 0.02 |
| Biophysical | 0.73 ± 0.05 | 0.70 ± 0.06 |
| L8 SR Bands + Texture | 0.89 ± 0.03 | 0.87 ± 0.03 |
| L8 SR Bands + Texture + Biophysical | 0.88 ± 0.03 | 0.86 ± 0.04 |

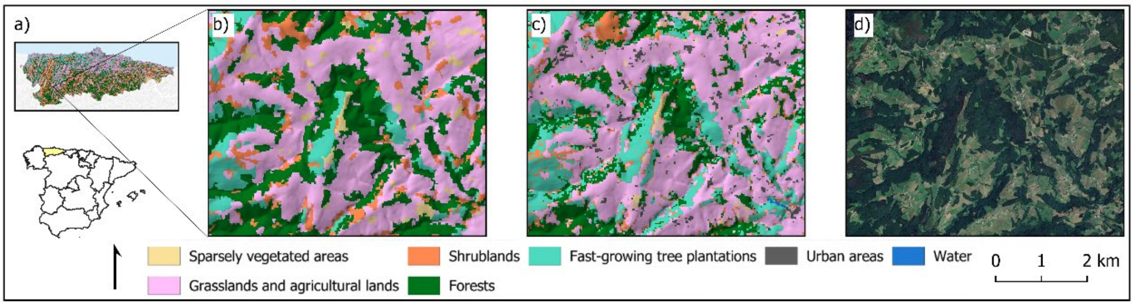


**Figure 1**. Land cover classification maps of the study area in 2023. (a) GEOBIA-based classification for the entire study area; (b) detailed view of the GEOBIA classification; (c) corresponding pixel-based classification detail; and (d) PNOA orthophoto from 2023

The GEOBIA approach increased the F-score for fast-growing tree plantations by 0.13 (Table 2). This improvement is likely related to the monospecific composition and well-defined boundaries of these stands, which are effectively captured by the SNIC algorithm through the grouping of contiguous pixels with similar spectral and spatial properties. The primary advantage of GEOBIA lies in its ability to mitigate the "salt-and-pepper" noise commonly observed in pixel-based methods, where high spectral variability within a class leads to fragmented and ecologically inconsistent maps (Yang *et al*., 2021). In this context, technical literature highlights that the seed spacing (size) parameter in the SNIC algorithm is critical for achieving optimal classification accuracy. Studies using comparable workflows show that classification accuracy is non-linear: it typically increases with object size until reaching an optimal peak and then declines rapidly due to under-segmentation, where multiple classes are merged into a single object (Yang *et al*., 2021). In the Asturian context, the high variability in the size and shape of natural vegetation patches makes universal parameterization difficult, explaining why the differences between pixel and GEOBIA methods are less pronounced for the other classes compared to plantations.

**Table 2.** Class-level F-scores comparing pixel and GEOBIA classifications for different predictor groups (Landsat surface reflectance, texture metrics, and biophysical traits) for the study period.

| Predictor group | Pixel (avg ± SD) | Geobia (avg ± SD) |
|---|---|---|
| L8 SR Bands | 0.83 ± 0.16 | 0.84 ± 0.11 |
| Sparsely vegetated areas | 0.92 ± 0.02 | 0.93 ± 0.03 |
| Grasslands and agricultural lands | 0.95 ± 0.01 | 0.92 ± 0.04 |
| Shrubland | 0.78 ± 0.06 | 0.73 ± 0.08 |
| Forests | 0.91 ± 0.04 | 0.89 ± 0.05 |
| Fast-growing tree plantations | 0.60 ± 0.20 | 0.73 ± 0.09 |
| Textures | 0.60 ± 0.21 | 0.61 ± 0.21 |
| Sparsely vegetated areas | 0.87 ± 0.02 | 0.83 ± 0.02 |
| Grasslands and agricultural lands | 0.72 0.04 | 0.74 ± 0.02 |
| Shrubland | 0.40 ± 0.09 | 0.42 ± 0.06 |
| Forests | 0.66 ± 0.08 | 0.68 ± 0.02 |
| Fast-growing tree plantations | 0.34 ± 0.06 | 0.33 ± 0.07 |
| Biophysical traits | 0.69 ± 0.15 | 0.67 ± 0.16 |
| Sparsely vegetated areas | 0.82 ± 0.05 | 0.80 ± 0.05 |
| Grasslands and agricultural lands | 0.80 ±0.08 | 0.78 ± 0.11 |
| Shrubland | 0.50 ± 0.08 | 0.46 ± 0.10 |
| Forests | 0.76 ± 0.02 | 0.77 ± 0.03 |
| Fast-growing tree plantations | 0.71 ± 0.20 | 0.56 ± 0.06 |

## 4. CONCLUSIONS

GEOBIA did not improve overall classification performance in the heterogeneous and dynamic landscape of Asturias, highlighting the sensitivity of this approach to landscape complexity and parameterization. However, it proved to be particularly useful for spatially well-defined, monospecific classes such as fast-growing tree plantations, which are important to monitor given their rapid expansion and landscape impacts in the area. The use of temporally invariant training polygons demonstrates the feasibility of long-term mapping with reduced manual effort. Overall, the limited gains from additional predictors suggest that Landsat spectral bands alone remain the primary driver of classification performance in heterogeneous landscapes, while GEOBIA adds value for structurally homogeneous vegetation types with clear boundaries. Evaluating performance along gradients of landscape heterogeneity would help disentangle the contexts in which object-based approaches yield tangible benefits.

## 5. ACKNOWLEDGMENTS AND FUNDING

This study was supported by the research projects LANDSUSFIRE (PID2022-139156OB-C22; Spanish Ministry of Science and Innovation, State Research Agency and FEDER); Severo Ochoa pre-doctoral contract from the Regional Government of Asturias (AYUD0029T01); research grant 'FIREPROs' (IDE/2024/000780) funded by the Principality of Asturias Government (Spain) and BIO10-PA (MRR-24-BIODIVERSIDAD-B10, Complementary Biodiversity Program (EU-funded Next Generation EU Recovery, Transformation and Resilience Plan). We also thank Paula Cembranos for proofreading and Miguel Menéndez for support with field surveys.

## 6. REFERENCES

Achanta, R., & Susstrunk, S. (2017). Superpixels and Polygons Using Simple Non-iterative Clustering. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 4895–4904. https://doi.org/10.1109/CVPR.2017.520

Arévalo, P., Bullock, E. L., Woodcock, C. E., & Olofsson, P. (2020). A Suite of Tools for Continuous Land Change Monitoring in Google Earth Engine. Frontiers in Climate, 2. https://doi.org/10.3389/fclim.2020.576740

Fernández-Guisuraga, J. M., González-Pérez, I., Reguero-Vaquero, A., & Marcos, E. (2024). Estimating Grassland Biophysical Parameters in the Cantabrian Mountains Using Radiative Transfer Models in Combination with Multiple Endmember Spectral Mixture Analysis. *Remote Sensing, 16*(23), 4547. https://doi.org/10.3390/rs16234547

López Trullén, D., Álvarez-Martínez, J. M., Sánchez Labrador, J. D., Jiménez-Alfaro, B., Pérez-Silos, I., Hernández-Romero, G., & Barquín, J. (2022). Espectrofenología con datos Sentinel 2: definición de curvas de referencia para la caracterización de ecosistemas forestales. *Ecosistemas, 2411*. https://doi.org/10.7818/ECOS.2411

Martin-Gallego, P., Marston, C. G., Altamirano, A., Pauchard, A., & Aplin, P. (2024). Mapping alien and native forest dynamics in Chile using Earth observation time series analysis. *Forest Ecology and Management, 560*, 121847. https://doi.org/10.1016/j.foreco.2024.121847

Pfitzer-López, D., Ramírez-Rodríguez, R., Roces-Díaz, J. V., Álvarez-Martínez, J. M., Quevedo, M., García, D., Jiménez-Alfaro, B., & Suárez-Seoane, S. (2026). A new index for monitoring non-linear trends in passive forest recovery at regional scale. *Ecological Indicators, 182*, 114532. https://doi.org/10.1016/j.ecolind.2025.114532

Verhulst, M., Heremans, S., Blaschko, M. B., & Somers, B. (2024). Temporal Transferability of Tree Species Classification in Temperate Forests with Sentinel-2 Time Series. *Remote Sensing, 16*(14), 2653. https://doi.org/10.3390/rs16142653

Yang, L., Wang, L., Abubakar, G. A., & Huang, J. (2021). High-Resolution Rice Mapping Based on SNIC Segmentation and Multi-Source Remote Sensing Images. *Remote Sensing, 13*(6), 1148. https://doi.org/10.3390/rs13061148

Zhu, Z., & Woodcock, C. E. (2014). Continuous change detection and classification of land cover using all available Landsat data. *Remote Sensing of Environment, 144*, 152–171. https://doi.org/10.1016/j.rse.2014.01.011