An open-source GeoAI workflow for mapping historic agricultural terraces

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Abstract

Historic agricultural terraces are important cultural and geomorphic features, but their spatial distribution is often poorly documented, especially in abandoned landscapes where woodland expansion obscures terrace morphology. This paper presents a fully open-source GeoAI workflow for semi-automatic terrace mapping from high-resolution LiDAR DEMs. The protocol combines predictors derived from terrain morphology and broader landscape context within a Random Forest classification framework. Two models were compared: a benchmark model based on topographic and geomorphological variables, and an extended model incorporating potential solar irradiance, soil erodibility and least-cost corridor density as proxies for agricultural suitability, slope management and accessibility. The extended model consistently outperformed the benchmark model, achieving higher accuracy, precision, recall, F1-score and class separability, while also reducing relative overprediction and omission error. These results show that terrace detection improves when local morphology is combined with predictors that reflect human land-use choices. The workflow provides a reproducible FOSS approach for mapping both visible terraces and those preserved beneath woodland canopy, not only for supporting heritage documentation but also offering potential insights for land degradation assessment and climate adaptation strategies.

1. Introduction

Agricultural terraces are among the most enduring anthropogenic modifications of landscapes worldwide. Used for centuries across diverse environmental and cultural contexts, they provide multiple ecosystem services, including soil erosion reduction (Meliho et al., 2021; Tarolli et al., 2014), enhanced water retention (Avni, 2022), and potential carbon sequestration (Chen et al., 2020). They also support different land use systems, from arable farming and polycropping to agroforestry and grazing. Their development reflects the interaction between geology, geomorphology, hydrology, agricultural practices and landscape history (Varotto et al., 2018). Terraces are also important heritage features, contributing to regional landscape character and forming part of UNESCO World Heritage landscapes across Africa, the Americas, Europe and Asia (Turner et al., 2021). For this reason, they have attracted increasing attention from ecologists, agronomists, historians, geographers and geoarchaeologists interested in their origin, development and abandonment over long timescales (Brown et al., 2021; Kinnaird et al., 2025). Dated examples show highly variable temporal and geographical trajectories, from first millennium BCE and medieval terrace systems in the Mediterranean to pre-Columbian terraces in the Andes and Maya Lowlands, rice terraces in East and Southeast Asia, and long-lived stone terrace systems in East Africa (Borisov et al., 2016; Chase and Weishampel, 2016; Gashure, 2024; Jiang et al., 2014; Mader et al., 2024; Turner et al., 2021).

Despite their ecological, agricultural and heritage importance, many terraced landscapes have been affected by abandonment and transformation, especially since the “*Great Acceleration*” of the 1950s (Steffen et al., 2015), when abandonment became increasingly linked to urbanisation and the movement of farmers away from mountain hinterlands (Turner et al., 2021, 2020). This creates a major documentation problem. Spatially explicit and comprehensive inventories of historic terraces are often lacking, while manual mapping based on field survey or visual interpretation of remote sensing data remains time consuming, difficult to replicate and particularly challenging in abandoned or forested areas where terrace morphology is partly obscured. As a result, reproducible methods for mapping historic agricultural terraces are needed to support field validation, heritage management and broader environmental assessment.

Automatic terrace mapping has progressed from optical image recognition to geomorphometric analysis and, more recently, machine learning classification. Optical approaches are effective where terraces display clear spectral and textural signatures (Zhang et al., 2017). However, they are less robust for narrow, atypical or abandoned features, especially where terrace boundaries are poorly defined or partly obscured. Except in arid or sparsely vegetated environments (Ziyadi et al., 2019), abandonment often promotes vegetation recovery, shrub encroachment or woodland regrowth, which can obscure historic terrace morphology and reduce the effectiveness of optical data alone. Digital elevation models (DEMs) derived from airborne Light Detection and Ranging (LiDAR) can help overcome this limitation, as they allow terrace morphology to be detected beneath vegetation cover. However, this potential is not uniform across all datasets. Detection performance depends strongly on survey design, point density, acquisition season and DEM quality, and can be substantially reduced when LiDAR data are of poor quality or were not acquired for this specific purpose (Godone et al., 2018). Increasing attention has therefore been given to geomorphometric approaches that extract terrace related morphology directly from elevation data.

Semi-automated methods based on open-source GIS tools have also been tested for terrace mapping. Using GRASS GIS (GRASS Development Team, 2025) morphometric modules and a 2 m DEM generated from LiDAR data, r.geomorphon was shown to partially identify larger terrace features, but with important limitations. These included poor detection of narrow terraces of approximately 5 m width, sensitivity to DEM resolution, reliance on expert visual parameter selection and limited quantitative validation or transferability assessment (Amodio et al., 2026). More recent machine learning approaches have attempted to improve the detection of terrace platforms by combining multiple data sources. For example, terrain information from LiDAR data, spectral information from orthophotos and Support Vector Machine (SVM) classification have been integrated to map agricultural terrace platforms (Tubog et al., 2025). This approach highlights the potential of machine learning for terrace mapping, but also shows that performance remains influenced by local terrain conditions, vegetation density and data resolution (Tubog et al., 2025).

Taken together, previous automatic and semi-automatic terrace mapping studies have relied mainly on optical, textural, geomorphological and topographical descriptors. However, agricultural terraces are not natural landforms, but constructed features created to meet agricultural needs. Their spatial distribution is therefore likely to reflect not only local terrain morphology, but also human decisions related to cultivation, accessibility, exposure and soil stability. Broader landscape variables, such as potential solar irradiance, soil erodibility and accessibility, have not yet been systematically incorporated into automatic terrace mapping, despite their relevance for explaining where terraces were built and maintained. This represents an important methodological gap addressed by the proposed protocol. By integrating broader environmental context predictors with variables derived from terrain morphology, the protocol extends approaches based only on visible texture or local geomorphometry. It is also entirely based on free and open-source software (FOSS), making it transparent, reproducible and adaptable to other landscapes. In contrast to optical approaches, which depend strongly on the visibility of terrace textures, the workflow reduces reliance on surface visibility and is better suited to landscapes where terraces are partly obscured by vegetation or abandonment. It also differs from rule-based geomorphometric procedures by using a Random Forest (RF) classifier capable of modelling nonlinear relationships between terrain variables and terrace occurrence. Finally, by producing spatially explicit classification outputs, the workflow supports field validation, heritage management and the integration of terraced landscapes into broader environmental analyses.

2. Study Area

The protocol proposed in this study was tested in the northern Apennines (Italy), in an area of 6800 Km^2 within the Tuscan-Emilian Apennines UNESCO Man and the Biosphere (MAB) Reserve (Fig. 1). This upland region preserves extensive evidence of historic agricultural terraces, woodland management and agroforestry systems, reflecting a long history of interaction between rural communities and mountain environments (Brandolini et al., 2023). The MAB reserve is characterised by steep slopes, dispersed rural settlements, mixed agricultural land, expanding woodland and remnant terraced systems that document former strategies of land use and slope management (Curotti, 2016). Within this cultural landscape, agricultural terraces are typically constructed on south- and west-facing slopes and are often faced with large blocks of local sandstone. Similar stone walls were also widely built along routes and between steeply sloping fields, where they served both to control soil erosion and to delimit tenurial boundaries (Fig. 1) (Brandolini and Turner, 2022). Although these features are not agricultural terrace systems *stricto sensu*, their construction techniques, functions and chronology appear to be closely associated with those of the terraces. They are therefore considered important components of the same landscape heritage.

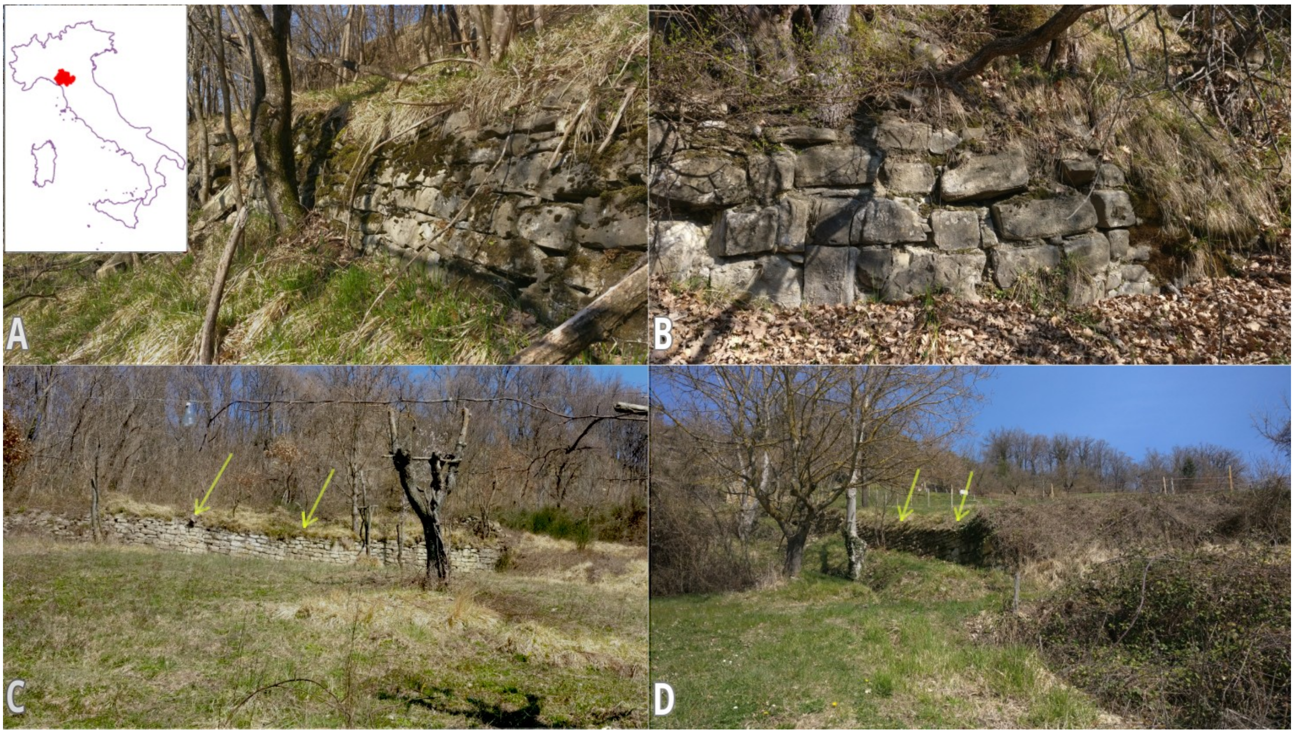

Figure 1. A and B: examples of abandoned historic agricultural terraces preserved beneath afforested canopy cover. C and D: examples of similar stone walls built between steeply sloping fields and along routes (yellow arrows).

Recent geoarchaeological research shows that terrace farming in the area was established mainly during the medieval period, between the 11th and 13th centuries CE, with phases of construction, renovation and maintenance continuing over several centuries (Brandolini et al., 2025). Since the mid-twentieth century, the northern Apennines have undergone major socio-economic and environmental change. Rural depopulation, agricultural mechanisation and the abandonment of marginal farmland have led to the decline of traditional land-management systems and to woodland expansion over formerly cultivated areas (Brandolini and Turner, 2022; Smiraglia et al., 2015). These processes are part of broader Great Acceleration transformations, during which industrialisation, demographic change and changing agricultural practices reshaped many European rural landscapes (McNeill and Engelke, 2016). In Italy, the abandonment of mountain areas and migration towards lowlands contributed to rapid reforestation and the progressive neglect of historic rural features (Brandolini, 2025a). Within the MAB Reserve, terrace abandonment has important implications for both heritage and environmental management. Although woodland expansion may provide ecological benefits, it can also reduce landscape heterogeneity, obscure historical land-use patterns and contribute to the loss of traditional ecological knowledge associated with terrace construction and maintenance (Antrop, 2005; Hjelle et al., 2012). Because large parts of the MAB Reserve remain only partially documented, the area provides a suitable case study for testing the semi-automatic open-source protocol proposed here.

3. Materials and Methods

The workflow was developed in Python to provide a scalable and transferable method for identifying anthropogenic terraced landforms in complex mountainous terrain. The protocol combines terrain morphometry, broader landscape predictors and supervised machine learning to map agricultural terraces from high-resolution LiDAR DEMs. LiDAR data were retrieved from the RER 2022 and RER 2023/24 datasets, freely available through the Geoportale Emilia-Romagna (Geoportale, 2025). The original 0.5 m DEM was resampled to 1 m before predictor generation to optimise computational efficiency across the full study area while preserving the geomorphological information relevant to terrace detection. This resolution was considered appropriate because the main terrace features in the study area are generally wider and higher than 1 m, and therefore remain detectable at the resampled scale. The predictor set included seven topographic and geomorphological variables: slope, plan curvature, profile curvature, roughness, topographic position index (TPI), topographic convexity index (TCI) and geomorphon. These variables were selected to describe the main morphological expressions of terraced landscapes, including flattened surfaces, risers, slope breaks and repeated microtopographic discontinuities. Three broader landscape predictors were then added: potential solar irradiance, least-cost corridor (LCC) density and soil erodibility. Potential solar irradiance was used as a proxy for solar exposure, while LCC density represented topographic accessibility and terrain connectivity. LCC density was calculated in GRASS GIS using r.walk and r.watershed from a regular grid of points; watercourses were inferred from flow accumulation and mildly penalised in the friction surface to reduce the overemphasis of riverbeds as movement corridors. Soil erodibility was represented by the RUSLE K factor from the Emilia-Romagna Region dataset and was included as a proxy for erosion susceptibility and potential slope instability (Geoportale, 2022). Training data were derived from a retrogressive Historic Landscape Characterisation (Turner, 2007) dataset developed within the MAB UNESCO area (Brandolini and Turner, 2022), and were refined through field observation and manual mapping of terrace and non-terrace samples. Terrace samples were buffered by 1 m and non-terrace samples by 5 m before rasterisation to extract labelled pixels for model training. Pixels with missing or invalid predictor values were removed before model fitting.

The resulting pixel-level dataset was used to train a RF classifier. RF was selected because it is well suited to remote-sensing and GeoAI applications involving noisy, high-dimensional and multicollinear data, and because it can model non-linear relationships among predictors (Belgiu and Drăguţ, 2016; Böhlen, 2024). This is particularly relevant for terrace detection, as terraces are not defined by a single morphometric parameter but by interactions among terrain morphology, environmental context and human land-use choices. The samples were split into training and test subsets using a stratified 80:20 partition. The RF classifier was implemented with 500 trees, a maximum tree depth of 20, entropy as the splitting criterion and class weighting to reduce the influence of class imbalance. A probability threshold of 0.70 was used to convert predicted terrace probabilities into binary terrace and non-terrace classes.

Two RF models were tested. Model A was the benchmark model and included only topographic and geomorphological predictors: slope, plan curvature, profile curvature, roughness, TPI, TCI and geomorphon. Model B extended the benchmark by adding potential solar irradiance, LCC density and soil erodibility, in order to test whether predictors linked to agricultural suitability, accessibility and slope management improved terrace detection. Each trained model was applied to the full study area using a tiled prediction strategy, producing a binary terrace map. Model performance was assessed using precision, recall, F1-score, overall accuracy and ROC AUC. These metrics were selected because overall accuracy alone can be misleading in imbalanced datasets, whereas F1-score and ROC AUC provide information on terrace-class performance and class separability (Naidu et al., 2023). Spatial reliability was assessed through a raster-based comparison of model-exclusive predictions and omission errors. The binary maps were compared by subtracting Model B from Model A, identifying areas classified as terraces by only one model. Positive values indicated terraces predicted only by Model A, while negative values indicated terraces predicted only by Model B. These model-exclusive positive predictions were used to assess relative overprediction. Omission error was estimated by comparing each binary output with the rasterised reference terrace dataset. Pixels mapped as terraces in the reference raster but classified as non-terraces by the model were counted as false negatives, and the false negative rate was calculated as the proportion of missed terrace pixels relative to the total number of reference terrace pixels.

4. Results and Discussion

The comparison of the two RF models shows that the inclusion of broader landscape predictors improved the detection of agricultural terraces when compared with the benchmark model based only on topographic and geomorphological variables (Table 1). Model B, which included the full selected predictor set, achieved the best overall performance, with an accuracy of 0.965, a terrace-class precision of 0.914, a recall of 0.615, an F1-score of 0.735, and a ROC AUC of 0.983. By contrast, Model A, based only on topographic and geomorphological predictors, performed less effectively overall, with an accuracy of 0.951, a terrace-class precision of 0.820, a recall of 0.500, an F1-score of 0.621, and a ROC AUC of 0.951 (Table 1). Although the relatively high ROC AUC of Model A indicates that terrain-based variables still provide useful discriminatory power, its lower recall and F1-score suggest that topography and geomorphology alone are less reliable for accurately delineating terrace features at the selected classification threshold. The relative importance of predictors further supports this interpretation (Fig. 2).

In Model A, importance was concentrated among variables derived from terrain morphology, especially profile curvature, slope, roughness, TPI and TCI, confirming that local hillslope morphology provides a strong basis for terrace discrimination (Fig. 2). In Model B, however, predictor importance was distributed across both geomorphological and landscape variables. Profile curvature remained the most influential predictor, but erodibility factor K, slope, roughness, irradiance, TPI, TCI, and least-cost corridor density also contributed to the classification (Fig. 2). This suggests that terrace occurrence is not explained by local topography alone, but is also associated with broader environmental conditions linked to soil erodibility, solar exposure, and potential accessibility. Since RF importance scores are relative within each model and sum to 1, they should not be interpreted as direct causal effects. Nevertheless, the inclusion of these additional predictors appears to provide complementary information, helping Model B improve both terrace detection and spatial reliability (Fig. 2). To assess the spatial behaviour of the two RF models, their binary prediction maps were compared using a raster-difference approach.

Model	Acc.	Prec.	Rec.	F1	Support	AUC	Overp.	Omiss.
A	0.95	0.82	0.5	0.62	3494	0.95	72.30%	27.06%
B	0.96	0.91	0.61	0.73	3494	0.98	27.70%	15.73%

Table 1. Performance and spatial reliability metrics for the two RF terrace-detection models. Acc. = overall accuracy; Prec. = terrace precision; Rec. = terrace recall; AUC = ROC AUC; Overp. = relative overprediction; Omiss. = omission error. Overp. reports the proportion of model-exclusive terrace predictions among all disagreement pixels: 72.30% for Model A and 27.70% for Model B. Omiss. is reported as the false negative rate; the corresponding raster-based recall is 72.94% for Model A and 84.27% for Model B.

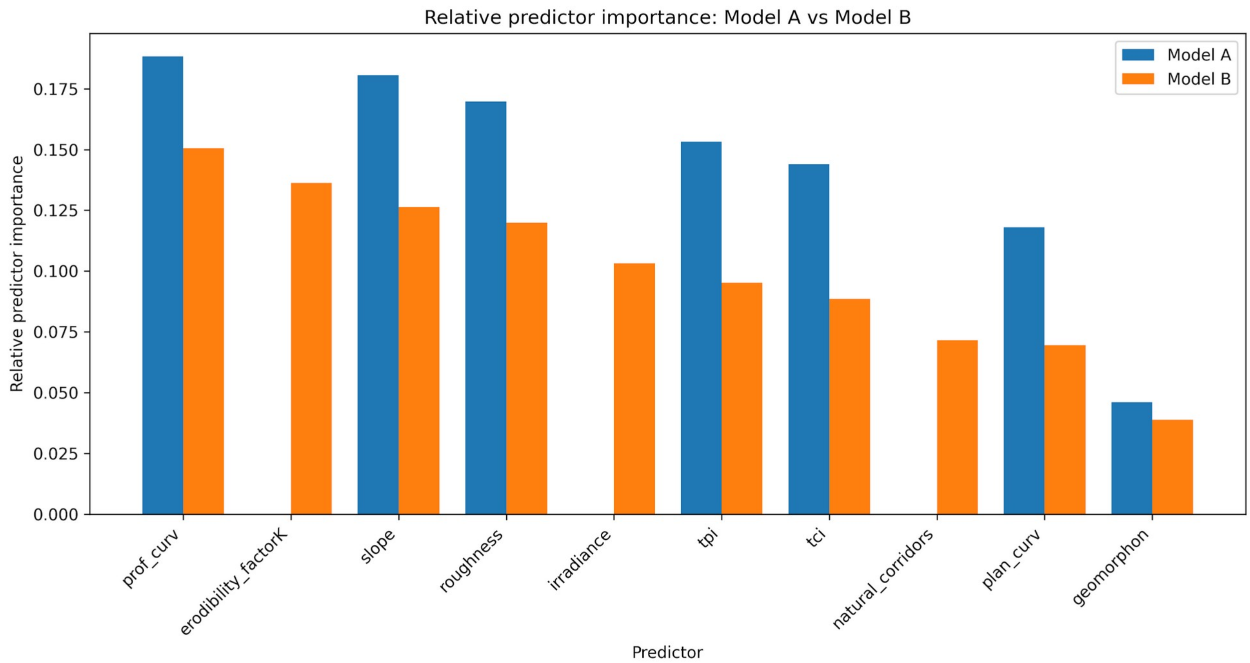

Figure 2. Relative predictor importance for Model A and Model B. The grouped bar chart compares the relative contribution of predictors used by the two Random Forest classifiers. Model A includes only topographic and geomorphological predictors, whereas Model B also includes erodibility factor K, irradiance, and Least-cost corridor density. The Y axis shows the unitless Random Forest importance score, with higher values indicating greater influence on terrace classification. Importance scores are relative within each model and sum to 1. Predictors shown only for Model B were not included in Model A.

Since both outputs covered the same study area and were aligned to the same prediction grid, subtracting Model B from Model A allowed areas classified as terraces by only one of the two models to be identified. Positive values indicate areas classified as terraces exclusively by Model A, whereas negative values indicate areas classified as terraces exclusively by Model B (Table 1). This comparison shows that Model A had a substantially higher tendency towards relative overprediction than Model B. Among all areas of disagreement, 72.3% were classified as terraces only by Model A, whereas 27.7% were classified as terraces only by Model B (Table 1). In relative terms, Model A produced 161.0% more model-exclusive positive predictions than Model B. Although these areas cannot be confirmed false positives without an independent validation dataset, the comparison provides a useful spatial measure of relative overprediction and suggests that Model B produced a more selective terrace map. This pattern is consistent with the comparison against the rasterised reference terrace dataset, which also indicates that Model B performed better in terms of omission error. Model B had a false negative rate of 15.73% and a raster-based recall of 84.27%, whereas Model A had a false negative rate of 27.06% and a raster-based recall of 72.94% (Table 1). Model A therefore showed a substantially higher omission error than Model B. This suggests that, despite its stronger tendency to produce model-exclusive positive predictions, Model A was less effective at consistently capturing the reference terrace features. Model B consequently provided a more balanced spatial prediction by reducing both relative overprediction and omission error. The analysis of model performance suggests that Model B produced a more accurate and spatially robust classification than the benchmark model. This indicates that the addition of landscape predictors improved both the statistical performance and the spatial consistency of terrace detection.

The visual comparison of the binary maps (Fig. 3) also shows clear differences between the two models, with Model B producing fewer isolated positive predictions and less general noise. Many of the model-exclusive positive predictions produced especially by Model A appear to correspond to modern road escarpments or other abrupt slope changes. Other features that both models tend to classify as terraces include tenurial boundaries and rural tracks bordered by earth banks or stone walls, which are morphologically similar to terrace features. Such structures were widely built along routes and between steeply sloping fields, where they contributed to soil erosion control and land boundary demarcation. Because their function, chronology and construction techniques are broadly comparable to those of agricultural terraces (Brandolini, 2025b), in this study they are treated as relevant contextual indicators of historic terraced landscapes, while remaining distinct from canonical terraces in the strict validation dataset. Furthermore, the better performance of Model B also offers useful insights for future semi-automatic and fully automatic machine learning approaches.

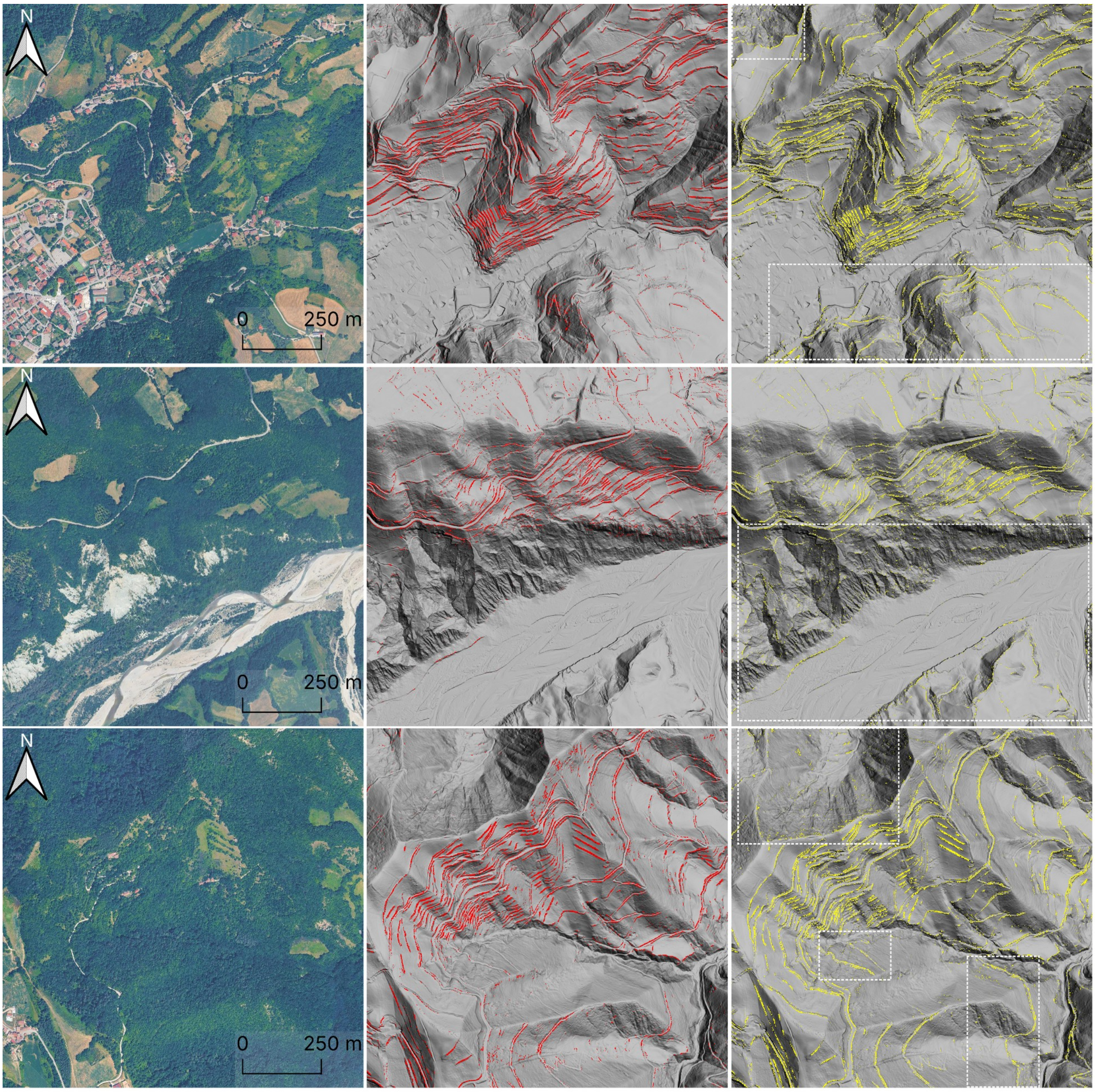

Figure 3. Visual comparison between Model A (in yellow) and Model B (in red). The white dashed boxes highlight areas where Model A produces model-exclusive positive predictions, especially along modern road escarpments and areas affected by pixel-level noise. Model B appears visually more precise and spatially cleaner than Model A.

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Since agricultural terraces are anthropogenic features built for cultivation, their location is not determined only by local morphology, but also by broader landscape choices related to agricultural suitability, accessibility and slope management. Landscape predictors such as irradiance, soil stability and accessibility (i.e. LCC density) can therefore act as important proxies for identifying these features. This is particularly relevant for abandoned terraces that are now completely hidden by vegetation. Previous studies have mainly focused either on the spectral signature of visible terraces in optical imagery or on geomorphometric parameters derived from DEMs, without fully considering the human-driven landscape logic that may help predict where agricultural terraces were built. Incorporating landscape predictors is therefore important not only for improving classification performance, but also for producing terrace maps that better reflect the historical and environmental conditions of terrace construction. Indeed, reproducible, spatially explicit terrace mapping is relevant beyond model performance because it can support archaeological documentation, heritage management and ecosystem service assessment.

In this study, many mapped terraces are located beneath forest canopy, confirming the value of semi-automatic methods for detecting historic landscape features that are difficult to identify through conventional imagery or rapid field survey. Abandoned terraces preserve evidence of former land management practices related to slope stabilisation, soil retention, water regulation and small scale agricultural adaptation. Their mapping therefore provides a spatial baseline for linking landscape history, environmental function and traditional ecological knowledge. This is particularly important for land-degradation and erosion risk assessment. In RUSLE modelling, the conservation practice factor (P factor) is often difficult to estimate because detailed spatial data on soil conservation features are unavailable. As a result, it is frequently omitted or generalised using land use and slope classes (Ghosal and Das Bhattacharya, 2020). Semi-automatic mapping of terraces can improve knowledge of the spatial distribution of these anthropogenic conservation practices and support more realistic regional P factor estimates. Furthermore, terrace mapping can be also relevant for estimating soil organic carbon stocks, especially where abandoned terraces are hidden beneath woodland. Terraces modify slope morphology, redistribute soil and create depositional environments where organic carbon may accumulate. Estimating the soil volumes stored within terrace systems is therefore a necessary step for assessing associated SOC stocks (Cucchiaro et al., 2021). However, SOC estimates require field measurements because they depend not only on SOC concentration, but also on soil depth, bulk density and coarse-fragment content (Djuma et al., 2020). A high-resolution terrace map does not replace field sampling, but it can make sampling strategies more targeted and spatially representative by identifying areas where anthropogenic soil accumulation is most likely. In this way, the proposed protocol can support more reliable assessments of carbon storage, erosion risk and climate mitigation potential in historic terraced landscapes.

5. Conclusions

This study demonstrates the potential of a fully open-source GeoAI workflow for the semi-automatic mapping of historic agricultural terraces in complex upland landscapes. By combining terrain predictors, broader landscape context variables and RF classification, the proposed protocol provides a reproducible method for identifying terrace systems that are difficult to document through conventional remote sensing or rapid field survey. The comparison between the two models shows that the inclusion of landscape predictors improved both classification performance and spatial reliability. Model B, which incorporated potential solar irradiance, soil erodibility and LCC density in addition to topographic and geomorphological variables, outperformed the benchmark model across all main metrics. It achieved higher accuracy, precision, recall, F1-score and ROC AUC, while also reducing relative overprediction and omission error. This confirms that agricultural terraces should not be modelled only as local morphological features, but also as the outcome of human decisions related to cultivation, accessibility, slope management and environmental suitability. The results also highlight the value of semi-automatic mapping for abandoned and terraced landscapes neglected by recent afforestation processes. Many of the mapped features are located beneath woodland canopy, where optical imagery alone is insufficient and where field mapping would be time consuming and difficult to replicate over large areas. In this context, high-resolution classification based on elevation and landscape predictors can provide an important spatial baseline for documenting historic rural land use systems, assessing their preservation and supporting future field validation.

Beyond archaeological and heritage applications, the workflow has wider environmental relevance. More accurate maps of terrace distribution could improve the representation of anthropogenic conservation practices in soil erosion models, particularly where the RUSLE P factor is omitted or generalised because of limited spatial information. The same spatial baseline can also support targeted soil sampling and more representative estimates of SOC stocks in terraced landscapes, especially where abandoned terraces may still store significant volumes of anthropogenic soil beneath vegetation cover. Overall, this paper shows that FOSS GeoAI approaches can make terrace mapping more transparent and scalable, while providing a workflow that can be tested for transferability in other environmental and cultural contexts. In doing so, semi-automatic terrace detection can contribute not only to the documentation of historic landscapes, but also to the integration of cultural heritage, land degradation assessment and climate mitigation research within a shared spatial framework.

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