Slope-driven edge analysis of high-resolution LiDAR data for automated detection of cultural terraces in Slovenia

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Abstract

Cultural terraces were often constructed to improve agriculture. Some terraces are still in use, while others have been abandoned. Knowledge of their locations is important for their preservation or potential reuse. There have been several attempts worldwide to create a register of terraces. In Slovenia, a suitable register has not yet been created due to heavy overgrowth and significant differences in cultural terrace types across different regions of the country. This research proposes detecting terraces using a LiDAR digital elevation model, geoinformation tools, and additional spatial data. The method detects sharp changes in slope data and creates polygons where such changes are detected in close proximity. The main advantage of the method is that it does not require any training samples yet still provides accurate results despite the diversity of terraced areas. We applied the method in Slovenia and achieved an accuracy of 91 percent, a precision of 76 percent, and a recognition value of 66 percent in one test area, and 92, 47, and 65 percent in another designated test area. To achieve higher accuracy, the input settings can be adapted to regional characteristics, which confirms earlier findings that terraces in Slovenia exhibit high diversity.

Keywords: terraced landscapes, feature detection, remote sensing, DEM, LiDAR, geomorphometry, Mediterranean, Slovenia

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Introduction

A crop terrace consists of a flat or gently sloping area of varying width and length, which has been recently or historically cultivated, and terrace banks of varying heights. Terrace slopes can be made of different materials; they may be grassed over, paved, or stabilised with stones (Titl, J. 1965; Drobnjak, V. 1990; Ažman Momirski, L. and Kladnik, D. 2009; Kladnik, D. *et al.* 2016). Knowledge of the location of cultural terraces is important for their maintenance, conservation, and further studies, such as analysing soil degradation (Pijl, A. *et al.* 2021). Knowledge of their location and other geographical features would improve our understanding of the reasons for the construction of cultural terraces and their ecological, social, and economic roles in the landscape (Ferrarese, F. *et al.* 2019). In Slovenia, based on similar international initiatives, Berčič, T. (2016) proposed the establishment of a database on the distribution of cultural terraces, which could be continuously updated. There are various ways of recording the locations of terraced areas, but the approaches can be broadly categorised into field mapping and mapping using GIS (geographic information systems) tools. Field mapping of terraced areas is time-consuming and expensive for larger areas. Difficult access, overgrown areas, and

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subjective recognition and interpretation of terrace areas are the main reasons why such field-based studies have only been conducted for smaller areas, either in Slovenia or abroad (e.g. Titl, J. 1965; Križaj Smrdel, H. 2010; Kladnik, D. *et al.* 2016; Zhang, Y. *et al.* 2017).

In addition to field surveys, terraces can also be recorded using computer techniques with various geodata. Different techniques for visualising the digital relief model can reveal cultural terraces in different ways. For visualisation, various methods can be used to represent the relief or surface, such as hill-shade, sky-view factor (Zakšek, K. *et al.* 2011), surface curvature (Koenders, R. *et al.* 2014), visualisation for archaeological topography (VAT) (Verbovšek, T. *et al.* 2019), and other geomorphological algorithms. The digitisation of terraces is only possible on the basis of these visualisations, but it can be influenced by subjectivity. These limitations have led to the development of various remote sensing methods for the automatic detection of cultural terraces, which are more or less successful in recognising terraced areas.

Terraces can be identified using different approaches such as:
- Object-based image analysis: Diaz-Varela, R.A. *et al.* 2014; Capolupo, A. *et al.* 2018; Sun, W. *et al.* 2019; Zhao, F. *et al.* 2021; Yu, M. *et al.* 2022.
- Canny edge detection method: Dai, W. *et al.* 2019.
- Machine learning based on object-based image analysis: Pijl, A. *et al.* 2020.
- Manual mapping: Pijl, A. *et al.* 2021.
- Edge detection on slope data: Sofia, G. *et al.* 2016.

The first comprehensive survey of terraces in Slovenia was conducted by Kladnik, D. *et al.* (2016), who manually digitised terrace areas from digital orthophotos. Using convolutional neural networks and learning patterns from the research of Kladnik, D. *et al.* (2016), cultural terraces were later identified by Glušič, A. *et al.* (2021) in southwestern Slovenia and by Ciglič, R. *et al.* (2024) for the whole of Slovenia. For smaller areas, terrace areas were identified using various relief representations in the Vipava Valley (Berčič, T. and Ažman Momirski, L. 2023) and the Jeruzalem-Ormož Hills (Pipan, P. and Kokalj, Ž. 2017). Edge detection was used to identify terraces in the Vipava Hills by Štaut, L. 2025.

Databases covering larger areas, such as the entire country (e.g. Kladnik, D. *et al.* 2016), are rare and often incomplete, for example due to terraces that are missing because they are covered by forest and therefore not clearly visible on orthophotos. Suitable methods for identifying cultural terraces are still being developed and often depend on the subjective judgement of researchers or on trial and error to achieve optimal results. Methods based on deep learning have been somewhat more successful (Glušič, A. *et al.* 2021; Zhao, F. *et al.* 2021; Lu, Y. *et al.* 2023; Ciglič, R. *et al.* 2024). However, deep learning methods require precise, numerous, and diverse training examples (Glušič, A. *et al.* 2021). In Slovenia, the study by Ciglič, R. *et al.* (2024) used datasets from Kladnik, D. *et al.* (2016) for this purpose, which were created by manually digitising terraced areas from digital orthophotos.

Due to the great diversity of cultural terraces, terrace banks are often discontinuous on the digital elevation model, making it difficult to distinguish them correctly from other similar small features. The methods used so far in Slovenia to recognise cultural terraces have produced results with a low success rate (e.g. Jaccard-index 0.13 by Ciglič, R. *et al.* [2024]) and have been associated with various problems related to the training samples. To date, no such accurate detection of cultural terraces has been achieved in Slovenia, as examples from abroad demonstrate (e.g. Spano, A. *et al.* [2018] – 70% detection success rate; Lu, Y. *et al.* [2023] – 84% success rate). One of the most suitable and fastest data processing methods for extracting terraces is surface slope analysis. Slope analysis has been used by many authors for visual mapping of cultural terraces (Berčič, T. 2016; Sofia, G. *et al.* 2016; Capolupo, A. *et al.* 2018; Spanò, A. *et al.* 2018). If the resolution of the digital elevation model is sufficiently high, it is also possible to capture smaller or narrower terraces that may not be visible on low-resolution digital elevation models.

By developing a new slope edge detection method for recognising terraces, we aimed to address the shortcomings of established detection methods. The aim of this article is to present a new method for detecting cultural terraces based on slope-based edge detection that does not use training samples, and to evaluate the detection success rate using previous cultural terrace research in Slovenia.

Methods

We developed a new method for cultural terrace detection *(Figure 1)* based on the identification of strong relief changes in slope data, as part of broader research on terraces in Slovenia. All calculations were performed using ESRI ArcGIS Pro 3.2 software with ModelBuilder. Using data from the 0.5 m × 0.5 m digital elevation model (Triglav Čekada, M. and Bric, V. 2015), we calculated the slope and detected sharp changes using surface filters. LiDAR data were acquired for the Slovenian Environmental Agency for the entire country between 2011 and 2015, with at least 2 points per m² for the first return; some areas were scanned with higher point density, ellipsoid height accuracy of 15 cm, and positional accuracy of 30 cm. By adding barrier features, we considered only the changes that are part of the terrace banks. By merging the detected edges based on neighbourhood and barriers, we obtained the final layer of cultural terrace areas.

Slope-based identification of edges in the relief

The slope tool in ArcGIS Pro 3.2 is a procedure that uses a moving window of 3 x 3 cells and calculates, for each cell, the rate of change in the horizontal (east to west, *dz*/*dx*) and vertical (north to south, *dz*/*dy*) directions from the central cell to each neighbouring cell. The results are usually expressed in degrees, using the following equation (ESRI, 2025):

$$Slope = \tan^{-1}\left(\sqrt{\left(\left[\frac{dz}{dx}\right]^2 + \left[\frac{dz}{dy}\right]^2\right)}\right)$$

where *dz*/*dx* is the rate of change in the horizontal direction, and *dz*/*dy* in the vertical direction relative to the central cell. We used the Slope tool with default settings.

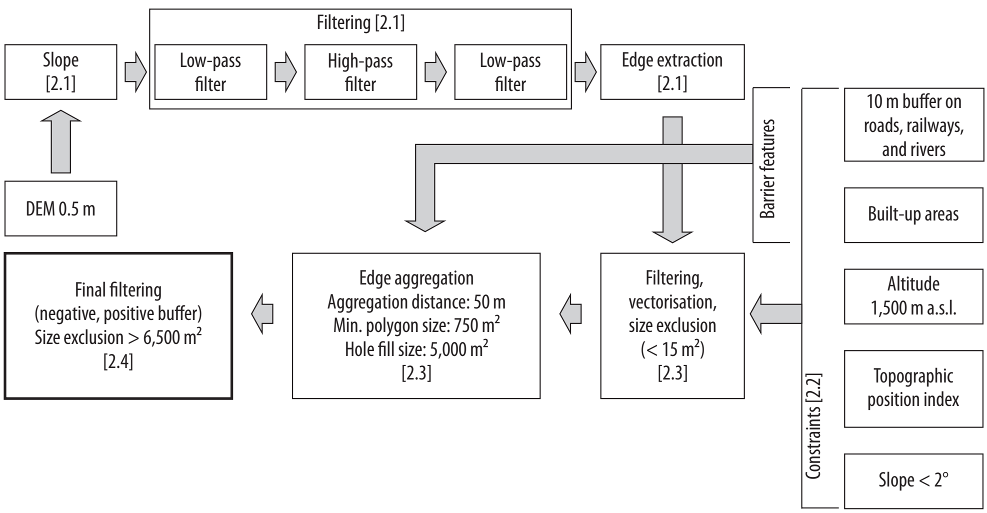

Fig. 1. Scheme of the research workflow. *Source:* Authors' own elaboration.

For further use, we require only data on the slopes, or the boundaries between the terrace bank and terrace platform. These are the locations where the slope changes significantly on the surface, but not on larger, non-flat areas with a uniform slope. Therefore, we applied a method combining low-pass and high-pass filters, which is also used in photography to remove blur (Susladkar, O. *et al.* 2022) and can be used to remove built-up areas from satellite images (Asal, F.F.F. 2019). A low-pass filter smooths the data by reducing local variance using a moving 3 × 3 cell window, thereby reducing noise. In this way, we smooth and eliminate minor changes on slopes that are not terraces, which appear to increase the range of steeper slopes around the terrace bank. By using a high-pass filter that emphasises the boundaries between objects, or where values change significantly between individual cells in a moving 3 × 3 cell window with a kernel sum of 0, we highlighted areas where the slope has changed. In areas where the slope is uniform, the raster values approach 0. The high-pass filter introduces more noise into the data. Surface irregularities too large to be eliminated in the initial smoothing process become visible again. Therefore, we reapplied a low-pass filter to the high-pass filter results to smooth these irregularities and apparently enlarge the area of detected slope change around the terrace banks *(Figure 2).*

Each terrace bank has two parts: an upper convex part and a lower concave part. After applying low-pass and high-pass filters, both parts were identified. Positive values indicate the convex part of the bank, while negative values indicate the concave part. The data obtained were visually inspected in five different areas: the Koper Hills, the Vipava Hills (Štaut, L. 2025), the Goriška Brda, the Jeruzalem-Ormož Hills, and the Posavje Hills,

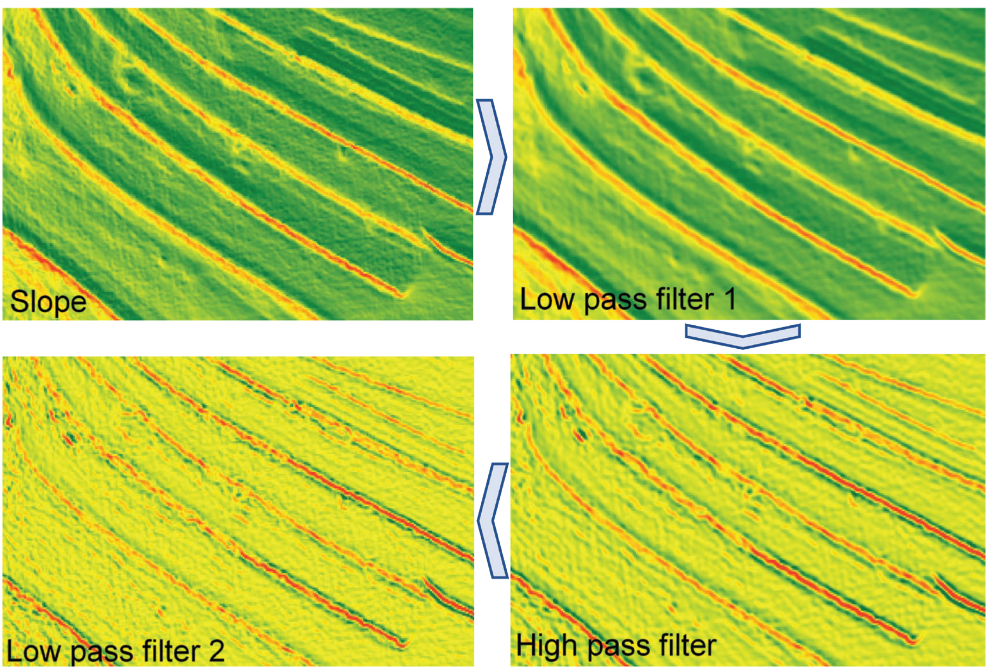

Fig. 2. Illustration of the individual steps of edge detection in the following order: calculation of the slope, application of a low-pass filter, application of a high-pass filter and re-application of the low-pass filter. *Source:* Authors' own elaboration.

to determine the threshold value distinguishing between edges on the convex and concave parts and to ensure that edges were detected on different types of terraces in various landscapes (Perko, D. *et al.* 2021). Values greater than 6 in the filtered slope data represented the areas of the convex part (edges), while all other cells (with negative values or values lower than 6) were assigned the value NODATA and were not used in further analysis.

Exclusion of areas based on additional data

At this point in the workflow, we have identified all edges that are sufficiently distinct on the surface. This includes edges that do not belong to terraces (e.g. road embankments, rocky outcrops, road ditches), which we excluded using constraints.

In this study, we focused solely on cultural terraces outside built-up areas, which is why we used the "built-up area and associated land" layer, the "roads and railways" layer, and the "watercourses" layer as constraints. For the Alpine hills area (Perko, D. *et al.* 2021), we also used the forest tracks layer as a constraint (Slovenia Forest Service. 2025). We applied a buffer of 10 m to the linear layers to capture strong changes in slope at the edges of roads or riverbanks.

According to Kladnik, D. *et al.* (2016), the highest terraces were found at altitudes up to 1400 m. The 2025 land use data from the Ministry of Agriculture, Forestry and Food indicate the highest marked arable land at about 1450 m. Therefore, we excluded all areas above 1500 m above sea level. Based on experience with remote sensing of cultural terraces (Zhao, F. *et al*. 2021; Ciglič, R. *et al*. 2024), we also excluded flat areas that do not exceed a slope of 2° on a 25 m digital elevation model (Ministry of Agriculture, Forestry and Food, 2026).

To eliminate pronounced slope changes in gullies and ridges, we used the topographic position index (TPI), which measures the elevation difference between the central point and the average elevation within a predefined range (*r*) (De Reu, J. *et al.* 2013). We used a radius of 60 cells (30 m) for *r*, which does not detect terrace banks up to a width of a few metres, but still detects other major changes on the surface. We categorised the TPI into three classes representing ridges, valleys, and flat surfaces or uniform slopes. TPI values between -1.1 and 1.5 (flat surfaces and uniform slopes), and less than -91.5 (floors of major valleys) were assigned the value NODATA and were not used as a constraint in further analyses. The remaining cells (with values from -91.5 to -1.1, representing gullies, and values above 1.5, representing ridges) were assigned the value 1 and used as one of the constraints. All input data, including the constraint and barrier features, are summarised in *Table 1*.

Table 1. Input and constraint features used in the research

Input data	Use	Resolution	Source
LiDAR	Edge detection, TPI	0.5 m	Slovenian Environmental Agency, 2015
TPI	Constraint feature	0.5 m	LiDAR (Slovenian Environmental Agency, 2015)
Roads	Constraint and barrier feature	Vector	Surveying and Mapping Authority of the Republic of Slovenia, 2025b
Railways	Constraint and barrier feature	Vector	Surveying and Mapping Authority of the Republic of Slovenia, 2025b
Rivers	Constraint and barrier feature	Vector	Surveying and Mapping Authority of the Republic of Slovenia, 2025b
Built-up area and related surfaces	Constraint and barrier feature	Vector	Ministry of Agriculture, Forestry and Food, 2025b
Forest tracks*	Constraint feature	Vector	Slovenia Forest Service, 2025
Slopes < 2°	Constraint feature	25 m	Surveying and Mapping Authority of the Republic of Slovenia, 2025a

*For Alpine hills only.

Edge merging

All constraint layers were rasterised at a resolution of 0.5 m and reclassified with the value 1 (constraint) and NODATA (no constraint), then aligned to the LiDAR data. The resulting layers were overlaid and summed with the layer of recognised edges. We retained all recognised edge cells where the value did not change. In the next step, the raster data were vectorised. Compared to the remaining noise in the data, terrace banks are relatively large linear spatial features that are close enough to each other to be merged based on proximity. We retained only polygons larger than 15 m². Smaller polygons usually represent noise in the data or minor relief changes that are not part of the cultural terraces. According to the literature (Titl, J. 1965; Drobnjak, V. 1990; Kladnik, D. *et al*. 2016), the vast majority of terraces in Slovenia are characterised by terrace platforms no wider than 50 m. The remaining edges were aggregated using the "Aggregate Polygons" tool, with barriers (see *Figure 1*) included to prevent polygons from merging across roads, railway lines, and built-up areas. The tool aggregated all detected edges closer than 50 m. During aggregation, it filled any holes smaller than 5000 m² and removed polygons smaller than 750 m².

Final filtering

The process of edge aggregation often produces narrow polygons that cannot be classified as terraced areas. Such errors, along with very small detected areas, were eliminated by applying a negative buffer of -10 m. The resulting layer was then assigned a 10 m buffer. In this way, polygons or parts of polygons narrower than 20 metres were removed. Based on the terrace platform width reported in the literature by Diaz-Varela, R.A. *et al.* (2014), the existing polygon sizes of terrace areas (Kladnik, D. *et al*. 2016), and a visual inspection of the test areas, all polygons with an area of less than 6,500 m² were also eliminated.

Analysis and evaluation of the terrace area identification

The obtained terrace area levels were used to calculate the areas and percentages of cultural terraces in Slovenian landscape types and administrative settlement areas. The results of the cultural terrace identification process were then analysed in two ways. The first, basic evaluation of the success of terrace area identification was carried out for two smaller areas *(Figure 3):*
– the area in the Vipava Valley, where terraced areas were mapped manually by examining the shaded relief (Berčič, T. 2016), and
– the Koper Hills area, using data from our own mapping of terraced areas, which we conducted by manually mapping terraced areas based on the analytical shaded relief of a 1 x 1 m digital elevation model.

The second evaluation of our results involved comparing them with the digitised terrace area data from Kladnik, D. *et al.* (2016). This evaluation was conducted for the entire country. We also repeated this comparison for the Koper Hills area, as we wanted to assess the accuracy of the only manually recorded terrace database for the whole of Slovenia.

For both the first (basic) and the second (comparison with Kladnik, D. *et al*. 2016) sets of terrace detection evaluation, we calculated quantitative indices: Jaccard-index, accuracy, precision, recall, and F1 score (Jaccard, P. 1912; Hicks, S.A. *et al.* 2022), which are commonly used to assess success rates in spatial analyses (e.g. Fisher, J.R.B. *et al*. 2018; Abdi, A.M. 2020; Kadyrov, R. *et al.* 2024). In this way, we were able to evaluate the accuracy of our method for detecting cultural terraces and to compare the results of our analysis with those of other studies.

Results

Characteristics of terraced areas and their distribution in Slovenia

Using the slope edge detection method, we identified 483.6 km² of terraced areas in Slo-

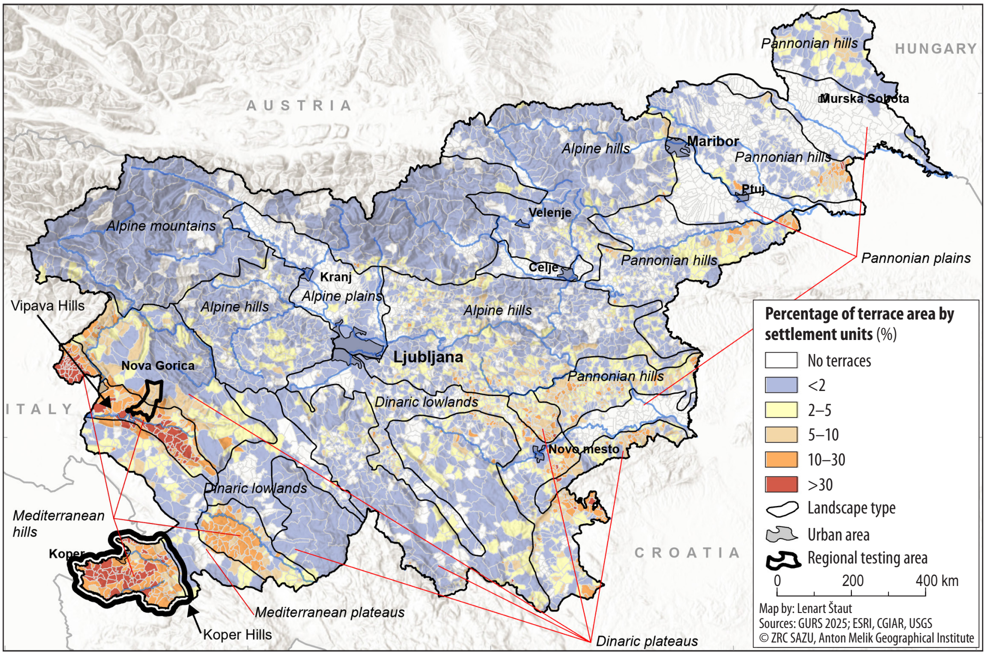

Fig. 3. Percentage of terraces by administrative settlement units. *Source:* Authors' own elaboration.

venia, representing 2.4 percent of the country (Štaut, L. 2025). The largest proportion of cultivated terraces is in the Mediterranean macro-region with 13.4 percent, followed by the Dinaric Alps with 2.2 percent, the Pannonian Basin with 1.4 percent, and the Alps with merely 0.7 percent.

The highest density of cultural terraces is found in the Mediterranean hills, with 0.26 km² of cultural terraces per km², while the lowest density occurs in the Pannonian plains. The Mediterranean hills account for as much as 45.1 percent of all cultural terraces, followed by the Dinaric plateaus with 16.4 percent, and the Pannonian hills with 12.3 percent. This distribution is also reflected in the proportion of terraced land within the administrative units of the settlements. In some units, more than 50 percent of the area is terraced. There are 40 such settlements in Slovenia, all but one of which are located in the Mediterranean hills. The settlement of Imenje in the Gorica Hills has the largest proportion of terraced land at 73.9 percent, followed by the settlement of Šmartno in the Gorica Hills with 70.5 percent, and Brdo in the Vipava Hills with 69.5 percent. Outside the Mediterranean hills, the proportion of terraced areas in the settlements is much lower. In the Mediterranean plateau type, the settlement of Tabor has the largest share (56.7%), while in the Pannonian low hills regional type, the settlement of Jeruzalem has the largest share (42.3%). In the Dinaric lowlands type, the settlement of Veliki Orehek near Novo Mesto has the largest share (39.5%), while in the Dinaric plateaus regional type, the settlements of Dolenje Nekovo (39.3%), Herinja Vas (35.8%), and Radovica (35.4%) have the largest shares of terraced land. In the Alpine hills landscape type, the highest proportion of terraced land is in the settlement of Straža pri Dolu (24.1%); in the Pannonian plain, it is in the settlement of

Norički Vrh (14%); in the Alpine mountains landscape type, in the settlement of Ravne (13.8%); and in the Alpine plain, in the settlement of Tunjice (4.2%).

The map (see *Figure 3*) shows six larger clusters where cultural terraces cover more than 20% of the settlement area. The largest proportion of such settlements is in the hinterland of Koper in the Koper Hills, the second in the area of the Vipava Valley and the Vipava Hills, and the third in the area of the Gorica Hills. In the south-east of the country, the areas under the Gorjanci Hills along the border with Croatia in White Carniola, as well as the areas of the Radulja Hills and the Krško Hills, stand out. In eastern Slovenia, the area of the Jeruzalem-Ormož Hills is notable. Within individual landscape types, there are significant differences in the density of cultural terraces. With the exception of the Mediterranean hills, these terraces occur locally in smaller areas and are not widespread across the entire landscape type.

Evaluation of the identification of cultural terraces

The basic evaluation was based on manually mapped terrace areas in the Koper Hills (own mapping) and the Vipava Hills (mapping according to Berčič, T. 2016) (*Table 2*). The highest overlap in terms of precision, recall, and F1 score was achieved in the Koper Hills, where the model correctly identified 66 percent of all manually mapped terrace surfaces. Similar results were obtained in the Vipava Hills, with 65 percent of areas correctly identified. The overall accuracy in both areas was just over 90 percent. The Jaccard-indices (see *Table 2*) were highest (0.54 out of 1) in the Koper Hills when comparing the terraces recognised by the slope edge detection method with the manually mapped terrace areas.

Table 2. Terrace identification performance in selected areas

Area	Koper Hills	Vipava Hills
Source of reference terraced areas	Own mapping	Mapping by Berčič, T. 2016
Accuracy	91%	92%
Precision	76%	47%
Recall	66%	65%
F1 score	0.71	0.55
Jaccard-index	0.54	0.38

As shown in *Table 3*, we calculated a confusion matrix for the area of the analysed settlements in the Vipava Valley. Using the slope edge detection method, we overestimated the areas of cultural terraces compared to the data from Berčič, T. (2016). We identified about 55 percent more areas than were mapped manually. We correctly identified 65.1 percent of terraced areas. The model did not recognise about 1 km² of the manually mapped terraces, which corresponds to almost one third of all manually mapped terraces.

We also presented a comparison of remote sensing and manual validation areas, with examples of common errors, for a smaller area in the Vipava Hills in *Figure 4* (see A, B and C inside). In the area marked with the letter A, the model overestimated the areas of cultural terraces. At this location, the sharp relief changes are due to the construction of

Table 3. Confusion matrices for terraced and non-terraced areas in the Vipava Hills

Vipava Hills		Slope edge detection, ha		*Total area*
		Terraced	Non-terraced	
Berčič's mapping	Terraced	186.29	99.86	*286.15*
	Non-terraced	208.14	3475.70	*3683.84*
Total area		*394.43*	*3475.56*	*3969.99*
		Slope edge detection, %		*Total percentage*
Berčič's mapping	Terraced	5	3	–
	Non-terraced	5	88	–
Total percentage		–	–	*100*

dry-stone walls. The situation is similar at site B, where a gully, which was not eliminated by the topographic position index, and traces of human alterations that are not cultural terraces are marked. At location C, the model did not recognise any cultural terraces, as the edges are not sufficiently pronounced. In the four settlements analysed, 10.7 percent of the settlement area is terraced according to the slope edge detection method, 7.8 percent according to Berčič, T. (2016), and 2.5 percent according to Kladnik, D. *et al.* (2016).

In the Koper Hills area, we detected 75.5 km² of cultural terraces *(Table 4)*, corresponding to 23.1 percent of the area. Manual terrace mapping, used as a reference for survey accuracy in this area, revealed 87.8 km² (26.9% of the area). Of the manually mapped cultural terraces, 57.6 km² (65.6%) match those identified by the slope detection method.

A visual comparison was made for a smaller section of the Koper Hills area shown in *Figure 5* (see D, E and F inside). In the area marked with the letter D, we identified cultural terraces that were not detected during manual mapping. This area contains anthropogenic structures in the form of dry-stone walls, which were recognised by the method. The area labelled with the letter E includes a gully that was not excluded by the TPI elimination process, or whose width is too small (less than 50 m), resulting in the merging of two polygons at the edges. In the area marked with the letter F, the model did not detect any terraces due to the proximity of the roads. The resulting polygon was too small or too narrow and was removed during the noise elimination process.

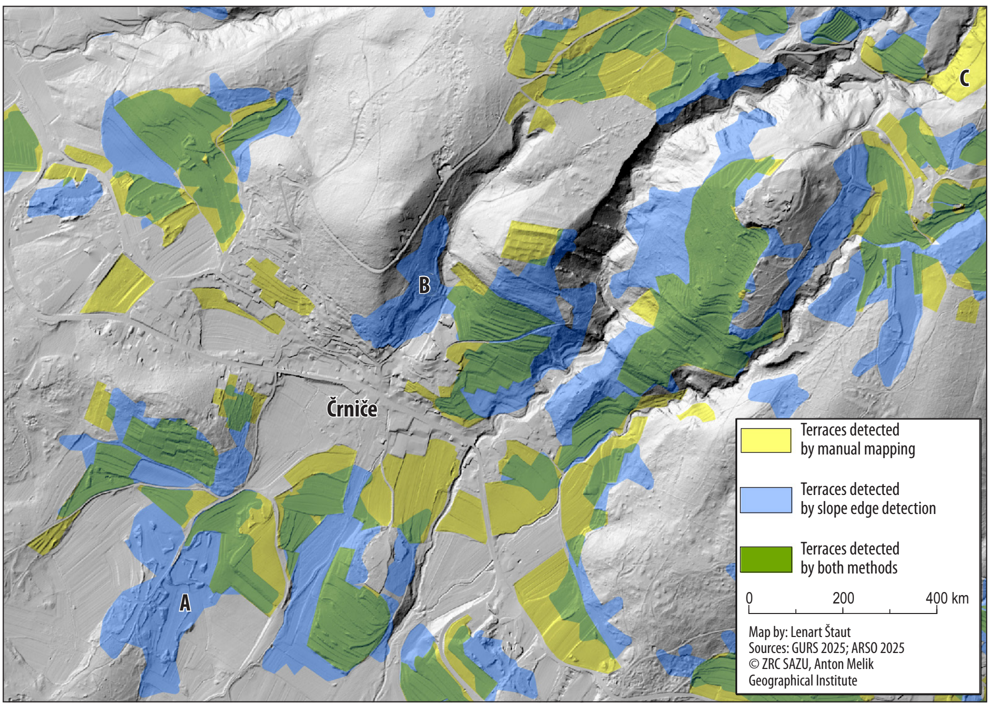

Fig. 4. Comparison of the results of manual mapping and the slope edge detection method in the Vipava Hills. *Source:* Authors' own elaboration.

Table 4. *Confusion matrices for terraced and non-terraced areas in the Koper Hills*

Koper Hills		Slope edge detection, ha		*Total area*
		Terraced	Non-terraced	
Manual mapping	Terraced	5,757.9	3,024.1	*8,782.0*
	Non-terraced	1,791.3	44,994.9	*46,786.1*
Total area		*7,549.1*	*48,019.0*	*55,568.1*
		Slope edge detection, %		*Total percentage*
Manual mapping	Terraced	10	5	–
	Non-terraced	3	81	–
Total percentage		–	–	*100*

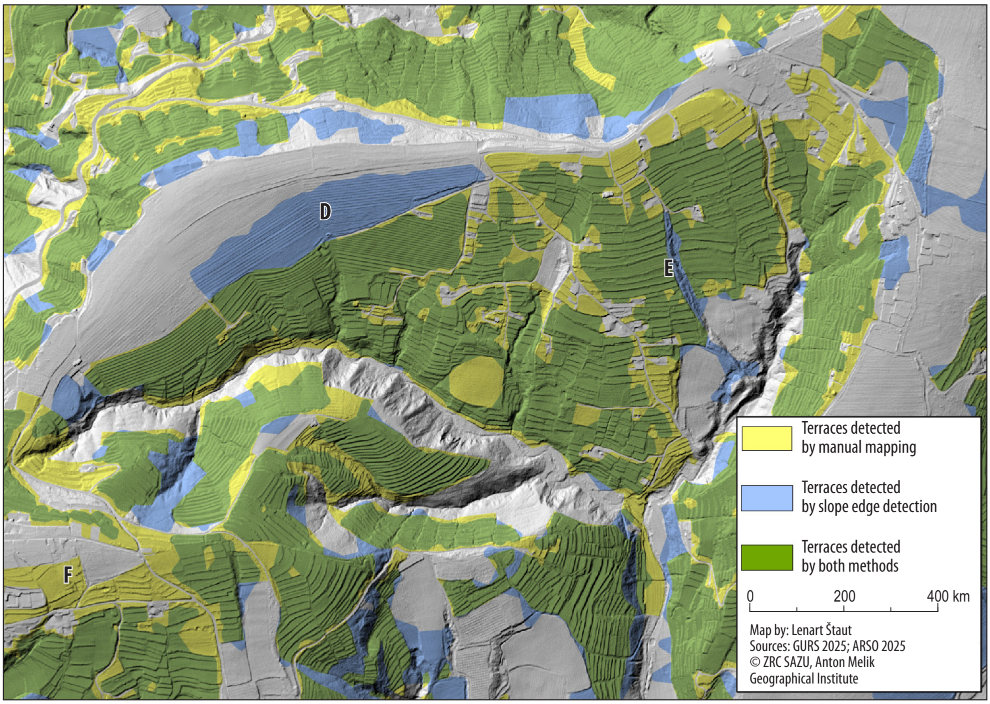

Fig. 5. Comparison of the results of manual mapping and the slope edge detection in the Koper Hills. *Source:* Authors' own elaboration.

Comparison with the existing terrace register

We compared the identified cultural terraces with the manually mapped terraces from the study by Kladnik, D. *et al.* (2016) for the entire territory of Slovenia. Despite some known shortcomings of this register, we aimed to assess the success rate *(Table 5)*, as it is the only nationwide database for terraces.

The relatively low overlap values in *Table 5* result from different approaches, particularly the disadvantage of the mapping of terraces

Table 5. Overlap of terraced areas according to the new method with the terraced areas for the entire territory of Slovenia*

Measure of accuracy	Value
Accuracy	97%
Precision	30%
Recall	45%
F1 score	0.36
Jaccard-index	0.22

*According to Kladnik, D. *et al.* 2016.

by Kladnik, D. *et al.* (2016), where, for example, areas under vegetation are missing.

To gain additional insights, we compared the manually recorded terraced areas on hillshade with those identified by Kladnik, D. *et al*. (2016) for the Koper Hills. Kladnik, D. *et al*. (2016) identified 58.2 km² of cultural terraces in this area, of which 44.5 km² (76.4%) overlap with our manually marked areas. Based on these data and the Jaccard-index (see *Table 2*), it is clear that the automatic detection method based on the digital elevation model was more successful in detecting cultural terraces than the manual mapping by Kladnik, D. *et al.* (2016), which relied only on orthophotos, topographic maps, and, in some cases, field observations, as we detected more cultural terraces. When comparing our manual mapping with the terraces identified by Kladnik, D. *et al*. (2016), the calculated Jaccard-index was 0.44, while the comparison between the slope detection method and Kladnik's mapping yielded an index value of 0.38. The highest overlap was found between the data obtained with the slope detection method and our own manually mapped terraces (0.54).

Discussion

Using the new slope detection method for recognising cultural terraces, which is based on edge detection on slope data, we identified 483.6 km² of terraces, or 2.4 percent of the area of Slovenia. Compared to the data on cultural terraces collected by Kladnik, D. *et al*. (2016) for the entire territory of Slovenia, we detected 161.9 km² more terraces. The difference in area is due to several factors. In our study, we used an automatic detection process sensitive to changes in relief. We detected smaller edges that may not belong to cultural terraces but can be falsely recognised as terraces when a large group of them is close together. Since we used the LiDAR DEM as input data, we were also able to detect cultural terraces beneath vegetation. Compared to Kladnik, D. *et al.* (2016), this is one of the main differences in the process of mapping cultural terraces.

Their data was based on manual mapping of cultural terraces using digital orthophotos and topographic map data. Therefore, their data mainly lacks cultural terraces under forest cover. Of the 483.6 km² of cultural terraces that we identified, 197.3 km² are under forest cover according to the land use data. This figure roughly corresponds to the difference between the areas of cultivated terraces determined by Kladnik, and the terraces defined in our research. The larger total area of cultural terraces that we detected with the slope detection method is also due to errors in automatic detection. Compared to the results of Ciglič, R. *et al*. (2024), we detected far fewer areas of cultural terraces with our method. They detected 1,397.2 km² of cultural terraces using machine learning, which is 913.6 km² more than we detected with our method. We conclude that the procedure according to Ciglič, R. *et al.* (2024) is too sensitive to small relief changes (drainage channels, arable land, minor surface irregularities), as the authors did not apply additional constraints to eliminate these shapes. A problem already highlighted by the authors (Ciglič, R. *et al.* 2024) is also the quality of the learning samples, which were based on Kladnik, D. *et al.* (2016) and therefore not sufficiently suitable for higher-quality machine learning.

The recognition performance of our method is comparable to the results of other approaches. Spanò, A. *et al.* (2018) recognised terraced areas at the regional level with a success rate of 70 percent, which is consistent with our success rates in the Koper Hills (65.6%) and the Vipava Hills (65.1%). Similar success rates (62.2% and 74.8%) were also obtained by Sun, W. *et al*. (2019) using object image analysis, while higher success rates of 87 and 90 percent were achieved using the U-net algorithm by Zhao, F. *et al*. (2021), and 96.9 and 98.4 percent by Lu, Y. *et al*. (2023). Ciglič, R. *et al*. (2024) calculated an accuracy of 89 percent on terraces, achieving a Jaccard-index of 0.68 for the area of Slovenia. Compared to our study, they achieved lower accuracy but a higher Jaccard-index. When comparing the results for smaller test areas (Glušič, A. *et al.* 2021; Ciglič, R. *et al*. 2024) and the Koper Hills area, which is comparable in terms of terrace density, the recognition results are similar *(Table 6).*

The newly developed method is not well suited to areas where the cultural terraces are not clearly visible (*Figure 6, e, f*). The slopes in such areas were excluded as noise due to their indistinctness, which could be improved in the future with settings adapted to the regional characteristics of the terraces. Forest tracks that are closer than 50 m on the slope and for which we did not obtain data on their location from the forest track register (2024) have a strong influence on the number of false-positive areas of the detected cultural terraces (*Figure 6, a, b, c)*. In areas where we had data on forest tracks and could therefore exclude them, there were far fewer false positives. Similar problems with forest tracks were also noted by Ciglič, R. *et al.* (2024). By using additional layers to delimit the areas where cultural terraces may occur, we were able to improve the quality of the data, similar to Spanò, A. *et al.* (2018). An additional problem can also be the quality of LiDAR data, where it shows relief changes caused by errors in data acquisition and preparation (Triglav Čekada, M. and Bric, V. 2015) (*Figure 6, d*).

Table 6. Basic success rates for the Koper Hills

Koper Hills	Slope edge detection	Testing area Ciglič, R. *et al.* 2024
Accuracy	91%	89%
Precision	76%	75%
Recall	66%	88%
F1 score	0.71	0.81
Jaccard-index	0.54	0.68

The terrace bank is typically a very small feature, usually no wider than a few metres (Berčič, T. 2016; Kladnik, D. *et al.* 2016). When the terrace bank consists of stones, its width on the digital relief model may be only one or two cells. The accuracy of the digital elevation model and the visibility of surface edges are also affected by vegetation (Triglav Čekada, M. and Bric, V. 2015). In our case, it appears as an interruption in the apparent line of the terrace slope.

The advantage of the slope edge detection method over other methods is that it does not require training samples and can be adapted to regional conditions with only minimal adjustments wherever LiDAR is available. In contrast, machine learning for terrace detection requires a large number of high-quality training samples (Zhao, F. *et al*. 2021; Lu, Y. *et al*. 2023; Ciglič, R. *et al*. 2024). The creation of training samples is also highly dependent on the accuracy of the person digitising, especially for a phenomenon as complex as cultural terraces, which do not have clearly defined boundaries (Van Coillie, F.M.B. *et al.* 2014; Berčič, T. 2016). Manual mapping of cultural terraces can be more accurate than other methods, but it is suitable only for smaller areas due to the time-consuming and potentially subjective nature of mapping cultural terraces (Kladnik, D. *et al.* 2016; Pijl, A. *et al.* 2021). Using the proposed method, we avoid these shortcomings by ensuring through initial method settings that it operates consistently in all areas, making the results independent of human influence. By using high-quality input data and appropriate constraint levels, we achieve similar accuracy more quickly. Cultural terraces in Slovenia, which are also highly diverse from a landscape perspective, vary greatly between regions (Kladnik, D. *et al.* 2016), and similar diversity is found worldwide (Diaz-Varela, R.A. *et al*. 2014; Sofia, G. *et al.* 2016; Kladnik, D. 2017; Yu, M. *et al*. 2022). By limiting the method to smaller homogeneous areas, we can adjust the sensitivity of the slope edge detection method. When applying the method to larger heterogeneous areas, as we did in our case, we adapted the

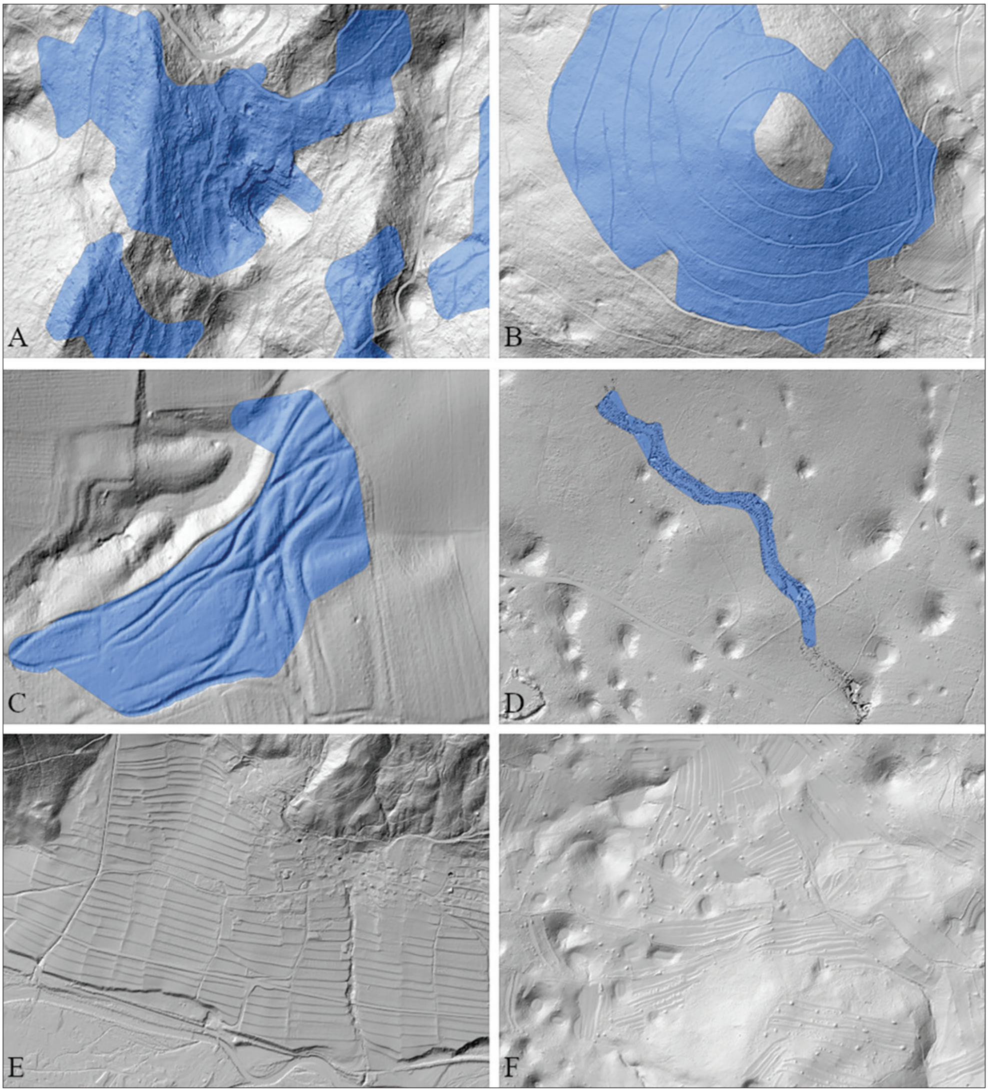

Fig. 6. Examples of false-positive (A–D) and false-negative (E–F) recognised terrace areas.
Source: Authors' own elaboration.

method to achieve the best average results, which can lead to overlooked or incorrectly identified terraced areas.

Conclusions

Terraced landscapes are found wherever humans have sought to increase land area for food production, reduce erosion, or enable mechanical cultivation of steep slopes. Many terraces have been abandoned for long periods and are now overgrown with vegetation. Therefore, accurate data on terrace distribution are important. In this paper, we demonstrate the performance of a new method for slope-based edge detection and aggregation on a LiDAR elevation model, without manual mapping or machine learning. We evaluated the detection of cultural terraces in selected areas. In the test areas of the Vipava Hills and the Koper Hills, we achieved overall accuracies of 91 and 92 percent, respectively, with recall values of 0.71 and 0.55. Compared to international studies (Spanò, A. *et al*. 2018; Lu, Y. *et al.* 2023), we achieved similar overall accuracy. Identification was most successful in areas where terraces were mechanically constructed at regular intervals (Pannonian hills) and in areas with well-defined, often stone-built banks (Mediterranean hills).

Outside these areas, there were more falsely recognised terraces despite the application of result filtering procedures. The analysis showed that, for more accurate recognition in all landscape types, the settings should be adjusted to regional characteristics and as many constraint layers as possible should be used. However, the results of the method, due to the speed of calculation and sufficient accuracy, can serve as a basis for collecting training samples in machine-learning recognition of cultural terraces.

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