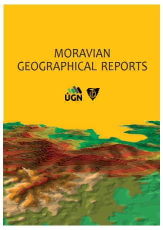

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Towards the deep learning recognition of cultivated terraces based on Lidar data: The case of Slovenia

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Abstract

Cultivated terraces are phenomena that have been protected in some areas for both their cultural heritage and food production purposes. Some terraced areas are disappearing but could be revitalised. To this end, recognition techniques need to be developed and terrace registers need to be established. The goal of this study was to recognise terraces using deep learning based on Lidar DEM. Lidar data is a valuable resource in countries with overgrown terraces. The U-net model training was conducted using data from the Slovenian terraces register for southwestern Slovenia and was subsequently applied to the entire country. We then analysed the agreement between the terraces register and the terraces recognised by deep learning. The overall accuracy of the model was 85%; however, the kappa index was only 0.22. The success rate was higher in some regions. Our results achieved lower accuracy compared to studies from China, where similar techniques were used but which incorporated satellite imagery, DEM, as well as land use data. This study was the first attempt at deep learning terrace recognition based solely on high-resolution DEM, highlighting examples of false terrace recognition that may be related to natural or other artificial terrace-like features.

Keywords: *cultivated terraces, deep learning, landscapes, digital elevation model, feature detection, Slovenia*

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1. Introduction

People build terraces into slopes to gain agricultural land, reduce soil erosion, reduce runoff, retain soil moisture, improve productivity, and provide gravity irrigation (Kladnik et al., 2005; Cicinelli et al., 2021; Slámová et al., 2015; Varotto et al., 2019; Zhao et al., 2021). A terrace comprises a flat or slightly sloping surface of varying width that is cultivated and a terrace slope (bank) of varying height (Ažman Momirski, 2008; Kladnik et al., 2016b). Lu et al. (2023, p. 2) defined terraces as "agricultural land with strip or wavy sections built on slopes greater than 2° along the contour direction". These cultivated landscapes can be defined as a complex landscape system influenced by various natural and socio-geographical factors. Cultivated terraces (also cultural or anthropogenic terraces) were originally often intended for agriculture and can be described in most cases as agricultural terraces. They also have invaluable cultural, historical, ecological, aesthetic, touristic, and scientific value (Camera et al., 2018; Djuma et al., 2020; Ferro-Vázquez et al., 2017; Terkenli et al., 2019; Zoumides et al., 2017).

Cultivated terraces vary according to the period of origin, natural conditions, form, land use, ownership, etc. Many countries feature cultivated terraces (Berčič & Ažman-Momirski, 2020; Cicinelli et al., 2021; Jinwen & Yuanyan, 2012; Kladnik et al., 2017a; Slámová et al., 2017; Varotto et al., 2019). They are quite significant in some areas, where entire stretches of land are designated as terraced landscapes, while they may be only visible upon closer inspection elsewhere (Kladnik et al., 2016b). Terraces can be active, inactive, or a combination of both (Berčič, 2016). Terraced landscapes are disappearing in places due to overgrowth (see also Gabrovec & Kumer, 2019; Moreno-de-las-Heras et al., 2019) or inappropriate management; however, they have been recognised as an important landscape element that needs to be protected and considered for revitalisation. Still, no clear criteria for identifying terraces have been developed and the management system is still fragmented in some areas, for example, in Slovenia (Kladnik et al., 2017b). Land abandonment and ageing of the owners are some of the reasons for the poor maintenance of terraces (Tarolli et al., 2019).

In order to efficiently combat the degradation of terraces in general, precise registers are needed that show the location and status of cultivated terraces. Maps are important for understanding the landscape (Gašperič, 2023); the overview of the locations of cultivated terraces is the basis for analyses of their ecological, social, and economic importance (Ferrarese et al., 2019) and can also indicate past agricultural land (Berčič, 2016).

Current data on terraced landscapes are not comprehensive. In the case of Slovenia, some cultivated terraces overgrown by vegetation were not recorded in the photo interpretation,

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topographic map analysis, and fieldwork in the earlier research by Kladnik et al. (2016b). Therefore, an important part of overgrown terraces might be missing and the most appropriate mapping methods using different datasets are still being developed. A review of past studies (see the following section for details) has revealed some gaps and opportunities for research:

- The deep learning recognition of cultivated terraces based solely on a digital elevation model has never been applied and tested for its robustness;
- Information on what kind of false recognition (false positives) and non-recognition (false negatives) can occur is still missing for different regions of the world, including the territory of Slovenia; and
- Recognition approaches based on digital elevation models (DEM) can be useful (and often the only possible method) in vegetated areas and countries where visual satellite or aerial imagery is less suitable for relief feature recognition.

To this end, our study focused on determining the optimal methodological approach for cultivated terraces recognition. The main objective of this study is to develop and test deep learning methods capable of automatically recognising cultivated terraces based solely on a high-resolution (1 m) digital elevation model. The study also examines the modelling results, points out potential problems, and provides suggestions on how to improve the training labels and modelling settings for further deep learning recognitions. Such approaches have not been used in Slovenia or anywhere else before, meaning the expected results are hard to predict.

It should be noted that since the current register of cultivated terraces in Slovenia is incomplete in some places where terraces are overgrown by dense vegetation, this also provides a real-life scenario to test the robustness of the deep learning to noisy training labels. This is an important computer-science research question for many recognition scenarios where accurate labels are hard to obtain. In addition, the results of the analysis can deliver important country-wide information on the location of unregistered terraces.

2. Theoretical background

In general, a number of international projects (Ferrarese et al., 2019; Scaramellini & Varotto, 2008) and studies on terraces have been done from different perspectives (Brown et al., 2020; Camera et al., 2018; D. Chen et al., 2021; Cicinelli et al., 2021; Deng et al., 2021; Varotto et al., 2019; Zoumides et al., 2017). To raise awareness about the importance of terraces, the Honghe Declaration was adopted worldwide in 2010 (Jinwen & Yuanyan, 2012). There have been many conservation efforts, analyses, and registration of terraces around the world, e.g. in Peru (Tillmann et al., 2020), China (Cao et al., 2020, 2021; Zhao et al., 2021), Japan (Kuroda, 2020), Italy (Pijl et al., 2021), and Slovenia (Kladnik et al., 2016b, 2017a). In 2010, the International Terraced Landscapes Alliance (ITLA) was established. Civil initiatives seek to recognise, protect, and conserve terraced landscapes, and some terraced landscapes have been inscribed on the World Heritage List (see Ažman Momirski & Berčič, 2016; Kladnik et al., 2017a).

Terrace recognition using satellite imagery was performed by Zhang et al. (2017). Their analysis used the Fourier transformation, edge characteristics, and a template matching algorithm. Sun et al. (2019) used satellite imagery to create a classification of terraced landscapes by using segmentation and k-nearest neighbour classification. Diaz-Varela et al. (2014) used a digital surface model and several spectral layers created from a UAV survey to perform an object-based image analysis and classification. As early as 2008, Ninfo (2008) used Lidar data to perform a terrace analysis using geoinformation methods to detect edges on a slope. The usefulness of Lidar data visualisations and analyses has been addressed more frequently recently (e.g. Alberti, 2020; Ferrarese et al., 2019; Romero-Martín et al., 2020; Tillmann et al., 2020). In Italy, a curvature analysis of the Lidar digital elevation model (DEM) and other DEM-derived variables have been used to detect terrace edges (Ferrarese et al., 2019). A similar approach was used by Cosner and Tecilla (2020) and Stralla et al. (2018). Ferrarese et al. (2019) also used other approaches, for example, visualising DEM data with manual mapping of terraces. Godone et al. (2018) determined terraces from Lidar data using a method based on the height and slope analysis technique developed by Scott and Pinter (2003) when studying coastal terraces. Berčič (2016) used orthophoto imagery, land use layer, and relief slope (generated based on LIDAR) to visually interpret terraces. Satellite imagery and DEM were used to detect terraces with a random forest classifier (Cao et al., 2021). Visual interpretation is still a very common approach (Alberti, 2020; Ažman Momirski & Berčič, 2018; Romero-Martín et al., 2020; Tillmann et al., 2020). In Slovenia, terraces have been documented based on a systematic visual examination of orthophotos, topographic maps, and fieldwork (Kladnik et al., 2016a; Kladnik et al., 2016b; Šmid Hribar et al., 2017).

In the last two decades, more and more deep learning methods have been used to solve various scientific problems. They have proven to be applicable in cases where classical models have not been able to solve the problem (Alavi et al., 2016). Image analysis using computer vision methods (e.g. convolutional neural networks) is a relatively new interdisciplinary field that is growing in popularity, especially for the analysis of visual spectrum images (Buscombe & Ritchie, 2018; Redmon et al., 2016; Ren et al., 2015). These methods have also been used in medicine (Ronneberger et al., 2015) and remote sensing imagery (Chen et al., 2019; Wurm et al., 2019). In terms of the type of structures (cultivated terraces) we want to recognise in our study, they are mostly areas of different shapes and sizes with certain textural features. For this type of data, semantic segmentation models have been utilised with great success. Recently, studies on terraces recognition with deep learning based on satellite imagery have been conducted for loess plateaus in China (Lu et al., 2023; Zhao et al., 2021). Lu et al. (2023) and Zhao et al. (2021) introduced deep learning methods for recognising terraces using satellite imagery and optimising their results with the help of predefined masking (e.g. to eliminate flat areas with DEM or non-agricultural areas with a land use map). A preliminary study on the recognition of terraces with deep learning based on Lidar data was also conducted for southwestern Slovenia by Glušič et al. (2021).

3. Methods and data

The study modelled cultivated terraces based on a) an existing Slovenian register of cultivated terraces (Kladnik et al., 2016b); and b) a Lidar digital elevation model (provided by the Slovenian Environment Agency; Triglav Čekada & Bric, 2015). The modelling was conducted in four steps (see Fig. 1). First, we prepared the data of DEM and the current terraces register as described in section 3.2. Then, we tested a deep model on a subset of the data (this part was further divided into training, validation, and testing stages) as described in section 3.3. In the last step, described in 3.4, we applied the model to the entire country and evaluated the country-wide results in two phases. In the first phase, we quantitatively examined the input and result layers; in the second phase, we systematically examined the result layer qualitatively (visually) and analysed discrepancies.

3.1 Research area and basic characteristics of cultivated terraces

Slovenia (Fig. 2) is a diverse country, even at the European level, as different landscape regions intertwine here, namely the Alps, the Pannonian Basin, the Mediterranean, and the Dinaric Alps (Ciglič & Perko, 2013). Almost two-thirds of the country is

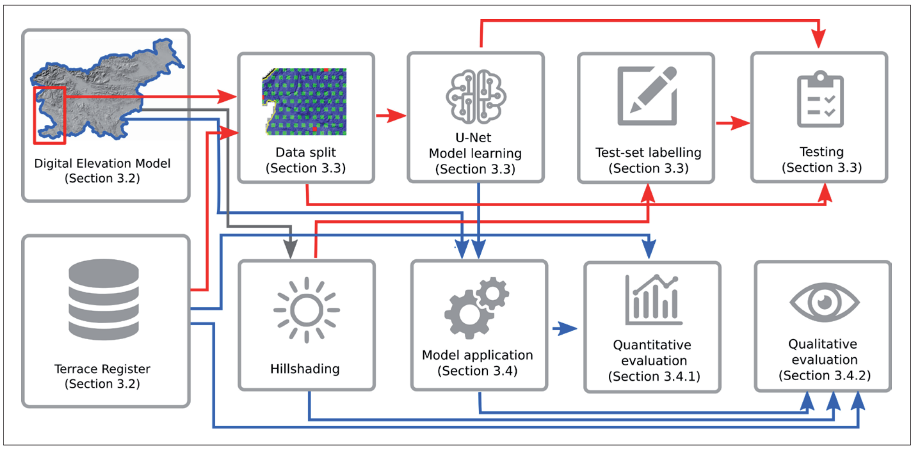

Fig. 1: Overview of the study workflow
Source: authors' conceptualisation

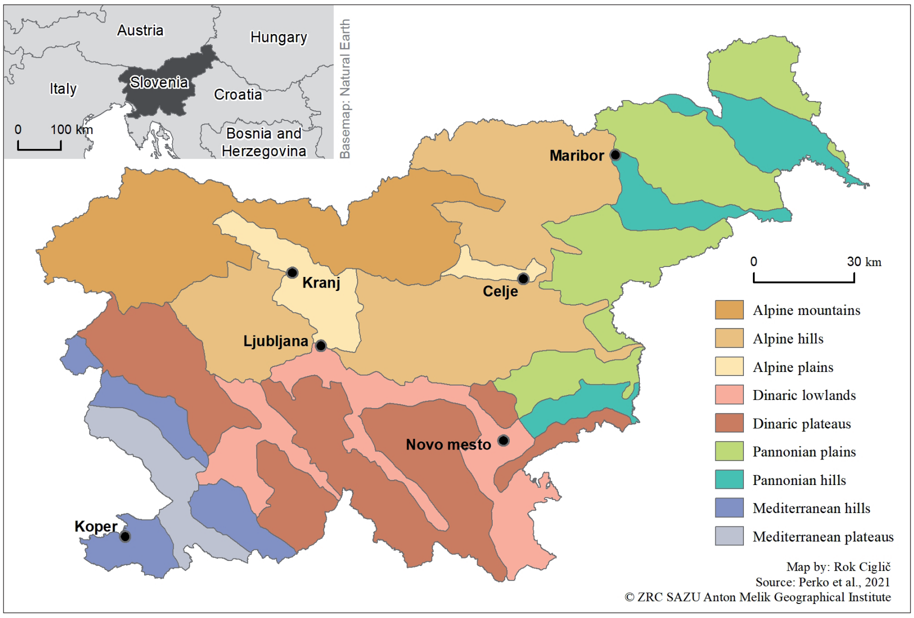

Fig. 2: Slovenian landscape types and location of Slovenia
Source: authors' elaboration based on Perko et al. (2021)

characterised by hills and mountains. More than 90% of the area is covered by loose sediments and sedimentary rocks; the greatest part of the country is composed of limestone. The country has a sub-Mediterranean climate in the southwest and a temperate continental climate in the central and eastern part and a montane climate in the northwest and north. The country has abundant water sources and forests cover approximately two thirds of the area; the widest spread form of natural vegetation are beech forests. Slovenia has just over 2 million inhabitants (Perko et al., 2020).

Terraced landscapes in Slovenia have been analysed in the past in the project 'Terraced Landscapes in Slovenia as Cultural Values' (Kladnik et al., 2016a; Kladnik et al., 2016b, 2017a; Šmid Hribar et al., 2017) as well as in other studies (Ažman Momirski, 2008, 2019; Ažman Momirski & Berčič, 2016; Berčič, 2016), constituting an important basis for further research with new methods.

The construction of terraces in Slovenia can be divided into two parts. Traditionally, terraces have been built in the Mediterranean parts of the country at least since the time of the Roman Empire for the cultivation of olive trees and vineyards. Until the 19th century, the terraced slopes were built with stones, but from then onwards, newer slopes were built without stones and were overgrown with grass. Land use also changed in different eras. Before the appearance of phylloxera, the terraces had a mixed land use with combined vineyards and fields on the same terrace. Later, the fields were replaced by vineyards and orchards planted on the banks of the terraces. With the intensification of agriculture in Yugoslavia, terracing also became more common in other parts of the country. While some of the old terraces on unfavourable slopes were abandoned, mostly in the period from 1963–1990 due to the depopulation of the countryside, many new terraces were created with the help of machines and are used almost exclusively for viticulture (Titl, 1965; Kladnik et al., 2016b, 2017a).

According to Kladnik et al. (2016b), terraces in Slovenia occur from 0 m to almost 1,200 m above sea level, with the majority of them located in Mediterranean parts of the country. They are most commonly found at a height between 200 m and 300 m on flysch rocks on slopes between 15.1% and 30%. The width of the terraces can range from around 2 metres on steep slopes to 50 metres on flatter terrain, while their length can vary from around 10 metres to several hundred metres in newer terraces (Drobnjak, 1989).

3.2 Input data

The model for the recognition of terraces was created by using the DEM and vector layer of the terraces register. The DEM was available with a resolution of 1 m and provided by the Slovenian

Environment Agency. The DEM layer is based on the Lidar point cloud with a ground return point density of at least 0.5 points / m^2 and at least 15 cm of vertical precision (Triglav Čekada & Bric, 2015). The vector layer of terraces register was created by manually digitising orthophotos and topographic maps, and through fieldwork done by the Research Centre of the Slovenian Academy of Sciences and Arts (Kladnik et al., 2016b). The layers of orthophotos (0.25 m and 0.5 m resolution) and various topographic maps were provided by the Surveying and Mapping Authority. In the evaluation process, a generalised land-use information (provided by the Ministry of Agriculture, Forestry and Food) were used for analysis of relationships between terraces and land-use. The generalised categories for land use were defined on the basis of vegetation height and land use; the combining of land use categories was done according to Gabrovec and Kumer (2019). A forest mask (also provided by the Ministry of Agriculture, Forestry and Food) was used to conduct the analyses with and without forested area.

3.3 Modelling

We based our modelling on an advanced machine learning framework of deep learning. Deep learning models can solve many different tasks in processing visual and auditory data by adapting the architecture of the model and training it with a given collection of training data. The main advantage of deep learning methods is that they mostly operate directly on the raw input and are able to learn autonomously to extract relevant features from a large amount of data that can be used to achieve the set goals (Sarker, 2021). Considering the nature of the input data (rasterised Lidar DEM) and the terraced landscapes (diverse landforms with a repetitive structure), we based our study on semantic segmentation models. These models accept a region of spatially connected inputs (e.g. a rectangular image patch) and predict a class for each unit, i.e. pixel. Specifically, we based our model on the U-Net architecture, which was first used for medical image analysis (Ronneberger et al., 2015), but has subsequently been utilised extensively in other segmentation domains as well (Stringer et al., 2021). The U-Net architecture is widely used due to its relative simplicity. It is based on the idea of a fully-convolutional combination of an encoder and a decoder. The skip connections (connections that bypass one or more layers in a neural network; He et al., 2016) between corresponding layers of both units improve the accuracy of the resulting segmentation. Our model architecture is shown in Fig. 3.

Based on preliminary experiments on a smaller dataset, we reduced the number of filters in individual layers and reduced the number of free parameters by 25% in comparison to the original architecture (Ronneberger et al., 2015). The change was done to promote generalisation and prevent overfitting to the training data. The reason for this is that reduced models are forced to use their parameters more efficiently and tend to find solutions that generalise better to new data. Of course, there is a limit to this phenomenon, as a model that is too small may not learn to solve a complex problem at all. We also took great care to represent the terrain elevation data in such a way that small elevation changes would be noticeable. Instead of using the elevation directly, we provided the model with partial derivatives over X and Y of the elevation raster. These two derivatives were computed using the Sobel operator. Together, the derivatives can be viewed as a different representation of the local slope (magnitude of the combined derivatives) and aspect (angle of the combined derivatives). The reasoning for using derivatives instead of absolute elevation is to have the input values distributed over a similar interval regardless of the location in the raster. This is an important requirement for successful training of deep models.

The model was implemented using the PyTorch framework (Paszke et al., 2019) and learned from randomly initialised weights using the Adam optimiser (Kingma & Ba, 2014) with a learning rate of 0.001. The batch size was set to 20 samples of 572 × 572 pixels. During learning, the process was monitored by observing the model performance on a validation set to detect overfitting and determine whether further learning was still sensible. We experimented with different loss functions and found that (soft) Dice loss (Dice, 1945) was best suited for our use case. This type of loss is robust to unbalanced data (significantly fewer cultivated terraces than areas that do not contain them). The final model was trained on a single NVIDIA Nvidia Titan X (Pascal) GPU for about 3 hours (40,000 steps).

Due to the size of the raster, patch-based processing was required. In the training phase, we randomly sampled batches of 20 patches from the allocated training area. An additional condition was set for the sampling procedure: A selected patch had to contain at least 1% of the terraced area (from the terraces register). This constraint served two purposes: a) it ensured the numerical stability of the loss function in the presence of highly unbalanced data; and b) since manual interpretations and mapping for the register might have missed some cultivated terraces (e.g. in densely vegetated areas), we used this technique to implicitly

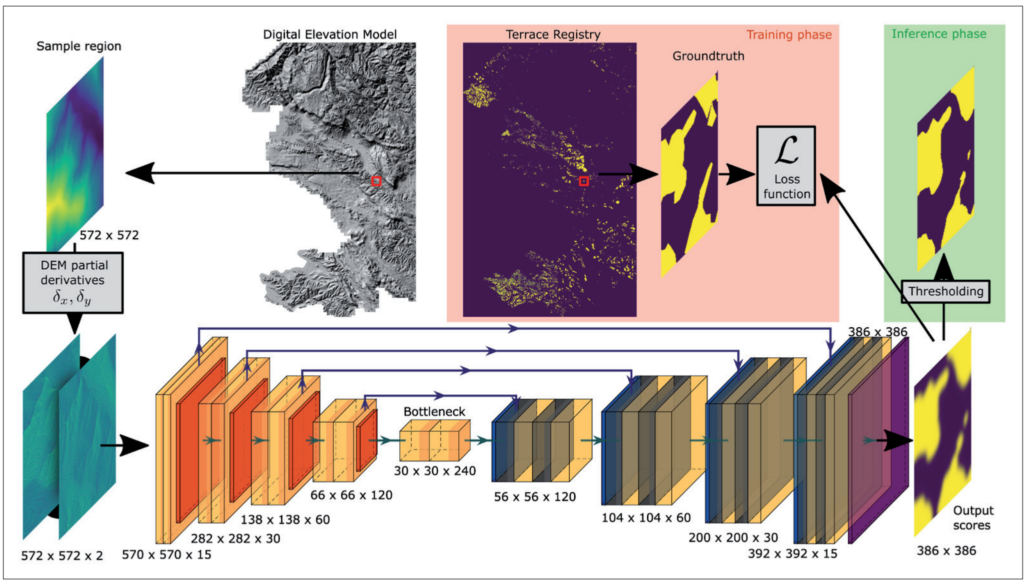

Fig. 3: Schematic representation of our segmentation model architecture
Source: authors' conceptualisation

avoid areas without terraces (e.g. mountains, flat areas) or areas where incomplete mapping might be present (e.g. forested areas). In the assessment phase, the raster was processed patch by patch in a scan-line algorithm. We also adjusted the padding to mitigate edge artefacts when joining individual patches back together.

The assessment of the model during and after the training phase was challenging due to inconsistencies in the labels used for training and the sensitivity of the classical overlap-based performance measures, frequently used when evaluating segmentation models. The assessment was therefore based on a mixture of validation on a larger subset reference data to determine overfitting and establish stopping criterion. The final test of the trained model was done on a smaller set of curated regions, not seen during the training. These regions were the only part of the data that was manually re-labelled (mapped) by the authors of this study using DEM and orthophoto references. The test data (test set) was used to establish an objective noise-free quantitative performance of the model and to observe how robust the model is to training noise. The selected quantitative measures for validation included accuracy, precision, recall, F1 score, and Jaccard index (Jaccard, 1912; Hicks et al., 2022). These measures have been frequently used in spatial analyses (e.g. Fisher et al., 2018; Abdi, 2020; Tang & Painho, 2023) and are all derived from the confusion matrix, but highlight different aspects of performance. The related equations are:

$$accuracy = \frac{TN+TP}{TN+FP+TP+FN},$$

$$precision = \frac{TP}{TP+FP},$$

$$recall = \frac{TP}{TP+FN},$$

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{2TP}{2TP+FP+FN},$$

$$Jaccard\ index = \frac{TP}{TP+FP+FN},$$

where *TP* denotes true positive pixels (correctly recognised as terraces), *TN* true negative (correctly recognised as not terraces), *FP* false positive (incorrectly recognised as terraces) and *FN* false negative (terraces, but not recognised).

Our model was trained in the region of southwestern Slovenia, shown in Fig. 4 (2,776.1 km^2; 13.7% of the country). The region was divided into chessboard-like patterns as training (73.8%), validation (25.3%), and testing sets (0.9%). The size of each rectangle was 2048 × 2048 pixels. One pixel corresponded to 1 m^2. The main property of the small test set was that it was manually re-labelled (mapped) using Lidar hillshade data and visually validated.

3.4 Application to the wider area and its evaluation

3.4.1 Overlapping

After obtaining the final model, which was validated and tested, we applied the model to the entire country (20,271 km^2). This allowed us to further assess its capabilities.

The evaluation consisted of two steps. By overlapping the terraces register and the computer-recognised terraces, we created a cross-tabulation and calculated the Jaccard Index, recall, precision (see 3.3 for the equations), as well as the kappa index. The kappa index is calculated by (Dettori & Norvell, 2020):

$$\kappa = \frac{p_o - p_e}{1 - p_e},$$

where p_o is an observed agreement and p_e is an agreement expected by chance.

These analyses were also carried out with a comparison of the location of the terraces with Slovenian landscape types (provided by Perko et al. in 2021) and land use data (provided by the Ministry of Agriculture, Forestry and Food).

3.4.2 Visual evaluation

An additional visual evaluation of the layer of recognised terraces was done by checking the shaded relief, which is commonly used for geomorphological features. It is based on a DEM that can be

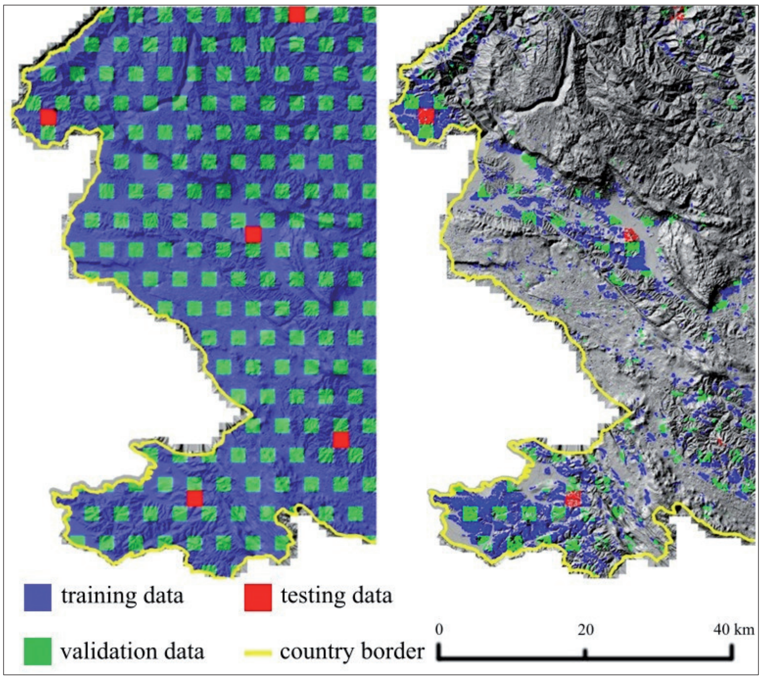

Fig. 4: Map of the area of the modelling phase (southwestern Slovenia) with a hillshade relief as the background
Notes: Left: the region was divided into training (blue), validation (green), and testing (red) sets. The yellow line denotes the country border. Right: the same visualisation, but with a focus on the terraced regions.
Source: authors' elaboration

illuminated under different conditions so as not to miss shapes oriented at the same angle as the illumination (Chandler et al., 2018). In this way, we were able to estimate examples of terraces that were not recognised or were recognised falsely (see Fig. 9). This step is crucial for further approaches to cope with recognition processes, as the training set may not have been complete and this was the first example of the application of deep learning methods to the entire territory of Slovenia. In order to perform a country-wide evaluation of the resulting layer, two samplings were conducted. First, we divided the country into a grid of 1 km^2 squares. Then, we randomly selected 0.5% of all the squares (118 in total) to perform a visual evaluation. In addition, 0.5% of the squares (64 in total) with the lowest Jaccard index were selected for an additional visual evaluation, focusing on the areas with the least overlap between the terraces register and the computer recognised terraces. As some terraces covered with forest had not been fully mapped by Kladnik et al. (2016b), the analysis of the recognition success was done only for the areas outside the forests.

4. Results

The results are presented in two parts: first, in the scope of the classical machine learning process of model building, where the performance is assessed on test splits. Second, we evaluated the application of the model to the novel data outside the training area (application to the entire country) and summarised the results quantitatively as well as qualitatively.

4.1 Evaluation of the trained model

The model was first assessed on the test split of the southwestern Slovenia region (marked as five red squares in Fig. 4). The terraces in these five regions were newly digitised on the basis of hillshade relief. This binary mask layer of the testing terraces was then compared with the terraces recognised by the deep learning model and with the terraces register (Kladnik et al., 2016b). The results are summarised in Table 1. It is evident that the original terraces register (by Kladnik et al., 2016b) has some differences from the testing set of terraces obtained by observing the Lidar hillshade data. Our trained U-Net model outperforms this original terraces register. This indicates that the training procedure is robust to noisy inputs (due to missing or misplaced reference labels). This is especially true for weighted measures that are less sensitive to imbalanced datasets, i.e. the Jaccard index and the F1 score.

We also observed the discrepancy in the precision and recall scores indicating that the layer of the terraces register by Kladnik et al. (2016b) is more conservative, probably due to the fact that some densely forested areas were not taken into account, while the deep learning model does not have this bias, which leads to better recall.

4.2 Application to the entire country

The final model was applied to the entire country of Slovenia. Note that the only reference we had in this case was the terraces register by Kladnik et al. (2016b). Besides computing the overall comparison that provided some insights into the model's performance, we also conducted an in-depth analysis of the discrepancies according to landscape types and land use categories (section 4.2.1) as well as a detailed qualitative comparison of selected areas (3.2.2). As already mentioned, some of the analysis in this part was performed for areas outside forests.

4.2.1 Confusion matrix and measures of success

After applying the model to the entire country, we prepared a confusion matrix (Tab. 2) and calculated several indicators of success rate to assess the model's capability in general (including all areas) and for non-forested areas only (Tab. 3). We noticed that most of the indices were similar. The highest difference was observed between the accuracy rates. The higher value comes from the analysis of all the areas, which could be expected since the majority of the area is non-terraced.

The Jaccard index for terraces recognition outside forests with our deep learning model was 0.13, the Kappa index was 0.22, the overall accuracy was 0.85, the recall was 0.78, and the precision was 0.16. We see that the overall accuracy is high, but this is still the result of a large proportion of actual non-terraced areas. The proportion of true terraces detected is just over three quarters, and the predictive power is low.

Both terraces layers, i.e. the terraces register (by Kladnik et al., 2016b) and the deep learning recognition of our study, showed a higher percentage of terraces in the western and eastern part of Slovenia. We calculated the percentage of terraced areas outside forests in a 1 km^2 grid for terraces register and for the terraces recognised by deep learning, respectively (Figs. 5 and 6).

The differences in terraces distribution across Slovenia (Fig. 5 and Fig. 6) indicated that there might be differences in landscape settings (appropriateness and needs) for terracing across the country. After comparing different Slovenian natural landscape types (Perko et al., 2021; Tab. 4), it is clear that the highest success rate for areas outside forests is associated with the Mediterranean part of Slovenia (Mediterranean hills and Mediterranean plateaus), which is located in western Slovenia where the training labels were taken. These two types are followed by the Pannonian hills (on the eastern edge of the country) and two Dinaric landscape types (Dinaric plateaus and Dinaric lowlands). The Mediterranean landscapes and the Pannonian landscapes are also the most terraced regions in Slovenia, according to Kladnik et al. (2016b).

	Accuracy	Precision	Recall	Jaccard	F1
Deep learning recognition (U-Net)	0.885	0.749	0.877	0.678	0.808
Terraces register by Kladnik et al., 2016b	0.850	0.784	0.633	0.539	0.701

Tab. 1: Quantitative results for the testing split. First row: comparison of the deep learning recognised terraces with the testing set of manually mapped terraces on a Lidar-based hillshade relief; second row: comparison of terraces register (by Kladnik et al., 2016b) with the testing set of manually mapped terraces on a Lidar-based hillshade relief
Source: authors' calculations

	Terraces register by Kladnik et al. (2016b)		Sum
	positive	negative	
Deep learning recognition positive	225.07 km^2 (2.69%)	1,172.10 km^2 (13.98%)	1397.17 km^2
Deep learning recognition negative	63.14 km^2 (0.75%)	6,921.93 km^2 (83.00%)	6985.97 km^2
Sum	288.21 km^2	8,094.03 km^2	100%

Tab. 2: Confusion matrices for non-forested areas in the entire country
Source: authors' calculations

	All areas (including forests)	Non-forested areas only
accuracy	0.93	0.85
Jaccard index	0.13	0.13
Kappa	0.24	0.22
recall	0.75	0.78
precision	0.16	0.16

Tab. 3: Comparison of basic success rates
Source: authors' calculations

Landscape type	Jaccard index
Mediterranean hills	0.44
Mediterranean plateaus	0.22
Pannonian hills	0.12
Dinaric lowlands	0.11
Dinaric plateaus	0.11
Alpine hills	0.08
Alpine plains	0.05
Pannonian plains	0.03
Alpine high mountains	0.03

Tab. 4: The Jaccard index for terraces recognition according to the Slovenian landscape types (according to Perko et al., 2021)
Source: authors' calculations

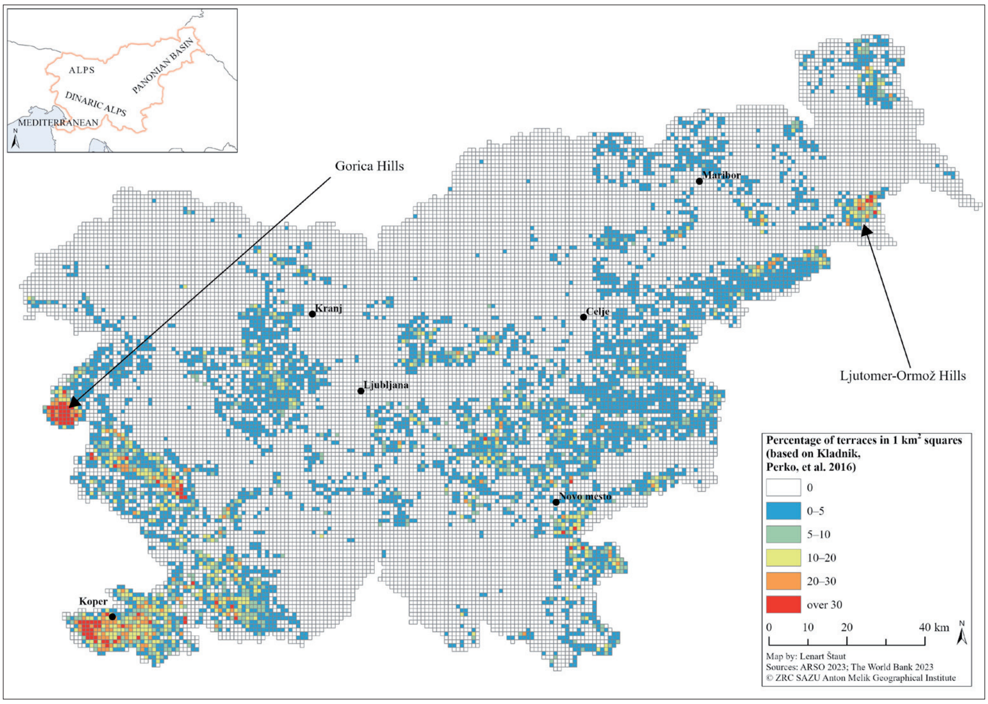

Fig. 5: Area of terraces defined in terraces register outside forests (shown as a percentage of 1 km²)
Source: authors' calculations

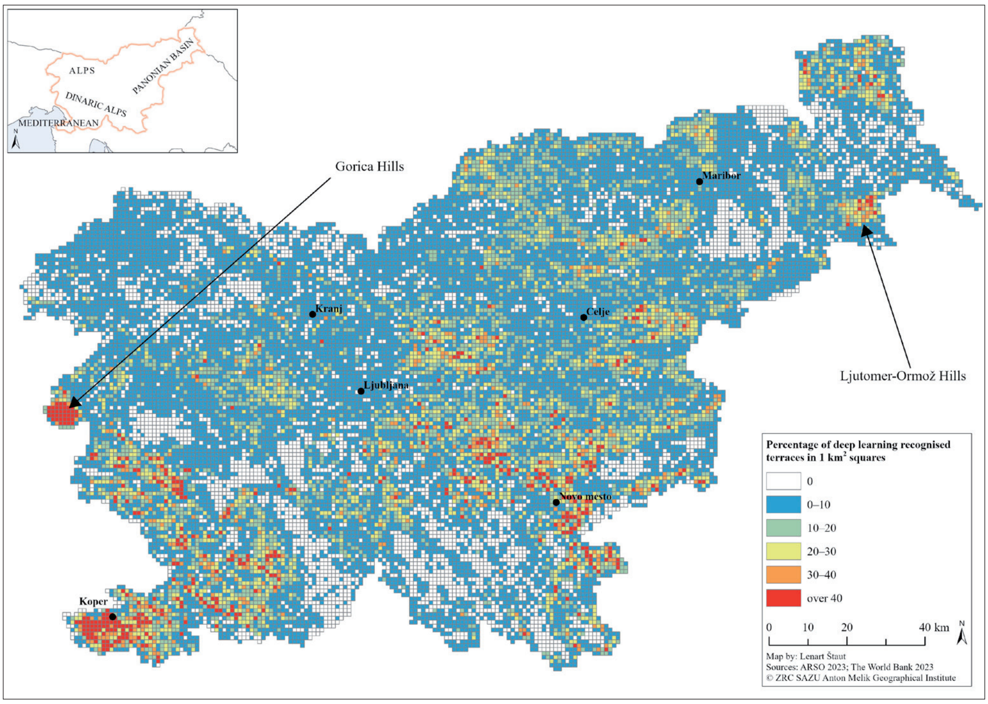

Fig. 6: Area of deep learning recognised terraces outside forests (shown as a percentage of 1 km²)
Source: authors' calculations

There are also differences in success rates outside the forests at a more detailed level between different regions of the country. We calculated the Jaccard index for 1 km^2 squares and found that most regions with well-preserved terraces, e.g. the Gorica Hills (Goriška brda) in the Mediterranean Hills in the west and Ljutomer-Ormož Hills (Ljutomersko-Ormoške gorice) in the Pannonian Hills in the east, had the highest success rate (Fig. 7). The terraces in the Gorica Hills are well maintained due to their importance in the regional economy. The area has intensive fruit and vine growing due to favourable warm Mediterranean climatic conditions. With the introduction of agricultural machinery in the past, the terraces became wider and more uniform. The slopes (banks) became more stable and noticeable (Kladnik et al., 2016b). Similarly, some parts of the Pannonian Hills have an intensive fruit and vine growing production due to a continental climate and low altitude above sea level. In this area, terraces are located in a thermal belt at higher relative altitudes. Therefore, the terraces are clearly visible for human interpretation of the aerial imagery or the hillshade relief. Obviously, they are also easily recognisable to the deep learning method. On the other

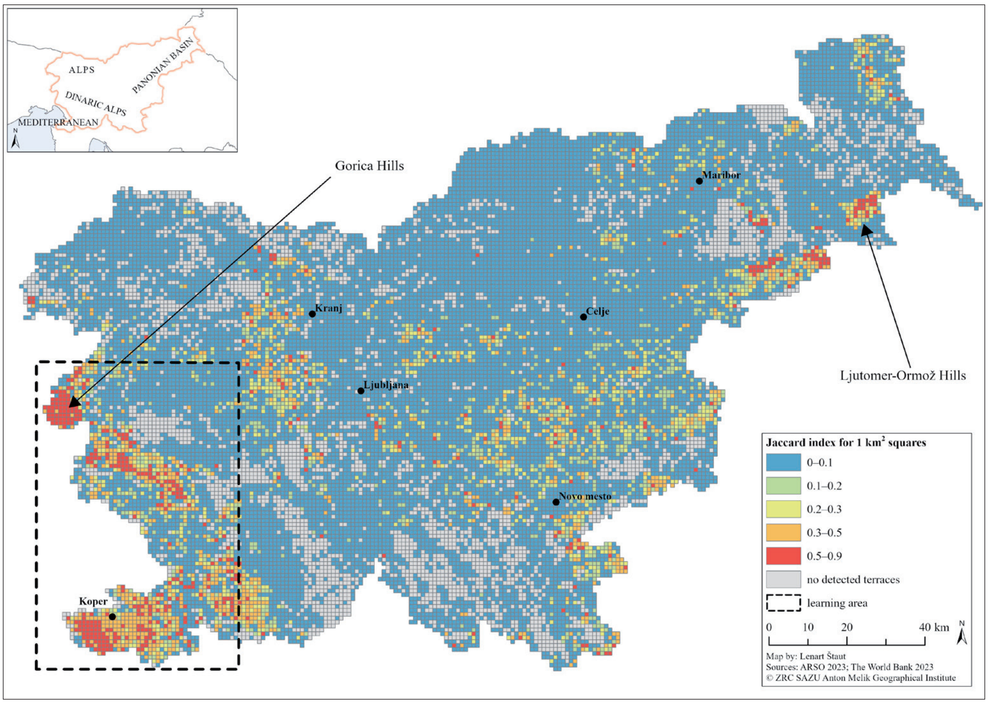

Fig. 7: Jaccard index for 1 km^2 (for non-forested areas). Regions in western and eastern parts of the country have the highest level of success rate
Source: authors' calculations

Fig. 8: Regularly maintained and well-visible terraces in Ljutomer-Ormož Hills (upper left; photo: Elena Odareeva, Adobe Stock) and Gorica Hills (upper right; photo: Marcin Juch, Adobe Stock). Less distinct terraces in Dinaric plateaus were used as fields in the past, but nowadays, they are covered with grass (bottom left; photo: Rok Ciglič) or sparse trees (bottom right; photo: Matevž Lenarčič). The photos have been used with authors' permission.

	Share of land use on terraces from the register [%]		Share of land use on deep learning recognized terraces [%]	
	forest included	without forest	forest included	without forest
Arable land	7.5	8.4	11.9	12.9
Vineyards	19.1	21.3	6.4	7.0
Other permanent crops	9.3	10.4	5.0	5.4
Grasslands	44.0	49.0	60.1	65.1
Other farm areas	7.5	8.4	4.4	4.7
Forest	10.4	–	7.8	–
Built-up area	2.1	2.3	4.3	4.6
Other	0.0	0.0	0.1	0.2
Total	100.0	100.0	100.0	100.0

Tab. 5: Relationship between terraces and different types of land use
Source: authors' calculations

hand, karst areas of Dinaric Alps are less favourable for farming in general due to high altitudes, lower temperatures, a thin soil layer, and the absence of surface water (Ciglič et al., 2013). Therefore, cultivated terraces and agricultural activity were generally quickly abandoned in the last decades and are therefore less visible in the landscape (Kladnik et al., 2016b). These areas have less distinct terraces now (e.g. gentle terraces in Dinaric regions covered with grass or sparse vegetation; Fig. 8).

We also examined the relationship between terraces and different types of land use (Tab. 5). We defined eight land use categories based on 2012 land use data. The results are presented for the terraces recognised by deep learning and the terraces register respectively. We repeated the analysis with forested areas excluded, as we assumed that terraces from the register are included in a lower percentage than those defined by the deep learning method.

Most of the terraces from the register are covered by grasslands, followed by those with vineyards. If we compare these results with the terraces recognised by deep learning, we see that these terraces are also most often covered by grassland, but there is a strong difference in second place with arable land instead of vineyards. In both cases, the third largest area is represented by forests.

4.2.2 Visual evaluation

Based on 118 randomly selected 1 km^2 squares and 64 randomly selected 1 km^2 squares with the lowest value of the Jaccard index, we gathered some observations on the success of deep learning recognition. Some areas were falsely recognised as terraces. This is because of various artificial shapes or features that look similar to agricultural terraces. For example, a road on a slope could be recognised as a terrace. Such a pattern with some smaller single terraces or single steeper slopes nearby can give an even stronger impression of a terraced area (Fig. 9A). Larger infrastructure elements, such as railway lines with embankments (Fig. 9B) or roads, especially those with repeated patterns of winding roads (Fig. 9C), can also be identified as terraces. In addition to these larger infrastructure elements, smaller paths on slopes, especially if they occur close together (e.g. due to grazing), can also be recognised as terraces. Small elevation differences due to different cropping structures (which influence the Lidar penetration to the ground) or different cultivation stages in the fields can be recognised as terraces (Fig. 9D). In some places, even barren agricultural land (fields) on the plain can be recognised as terraces (Fig. 9E), characterised by a repeating pattern of small 'ridges' and 'valleys'. The general landscape structure (mosaic) also influences the recognition algorithm, which recognises larger areas of terraces than they actually are. Some foothills of slopes with only one (large and distinct) edge were falsely recognised as larger terrace areas (Fig. 9F). On the other hand, some terraces are less pronounced and are crossed by non-terraced (but rough) relief, so that larger areas are identified as terraced.

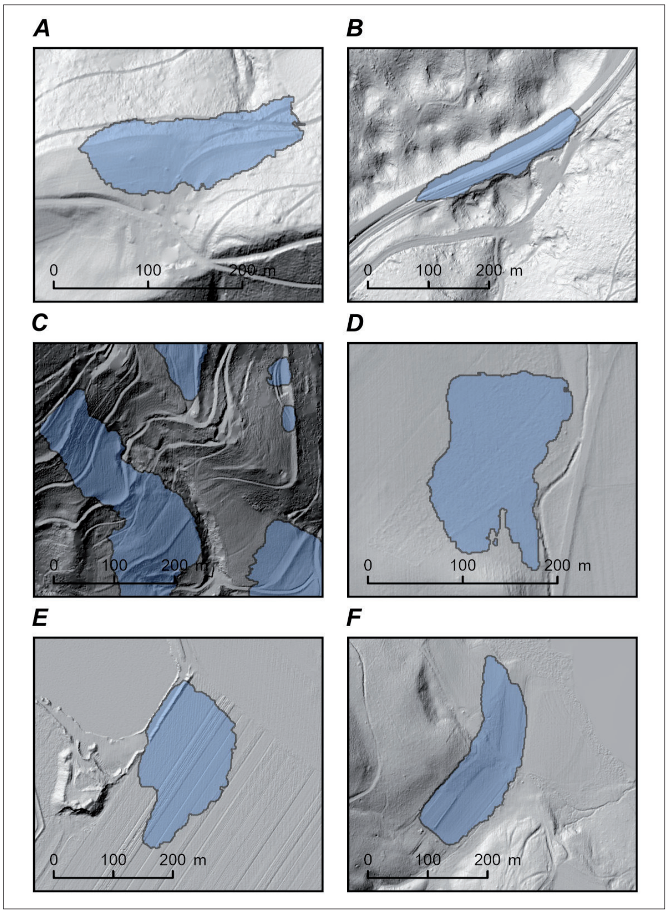

Fig. 9: Examples of falsely recognised terraces
Source: authors' calculations

After the visual examination of our results, it seems that deep learning recognition overestimated the number of terraced areas in the case of Slovenia. On the other hand, some terraces were not recognised by the deep learning method. There are cases where certain terraces or parts of them were not recognised by the model, which raises the need for further tuning the model or improving the training labels.

5. Discussion

In his study, Berčič (2016) predicted that recognition using machine learning could not be far off. Past studies (e.g. Cao et al., 2021; Glušič et al., 2021; Lu et al., 2023; Zhao et al., 2021) and our analysis support this prediction.

A comparison with some recent studies with machine learning approaches puts our work in a broader context. Cao et al. (2021) used several multispectral Landsat satellite images, GlobeLand30, Google Earth imagery, and a SRTM digital elevation model to create a classification algorithm (random forest classifier) for terraces in China. The overall accuracies were 94.7% and 88.4% (after additional visual inspection) and the Kappa indices were about 0.71. The analysis was performed at 30 m resolution. Zhao et al. (2021) used a deep learning-based U-net approach and a spectral angle mapper approach for three study areas in China. Terraces were recognised based on Google Earth imagery and refined by DEM (produced by drone imagery with 1 m resolution). The first method provided an overall accuracy of 87 and 90%, the second 40 to 49%. Lu et al. (2023) used Google Maps satellite imagery and the U-net algorithm for terraces recognition; afterwards, digital elevation model, GlobeLand30, and vegetation correction data were used for corrections. Their overall accuracy was between 96.4 and 98.4% (depending on the processing stage). In contrast to these studies, our study was based solely on the Lidar DEM and existing terraces register (by Kladnik et al., 2016b), which was not entirely accurate. No satellite or aerial imagery was used in our process, as well as no post-processing using expert knowledge. We were interested in defining terraces even in heavily vegetated areas where terraces cannot be observed without Lidar technology as well as in studying the limits of using deep learning alone for the task. This means our method was a novel approach and these first results were consequently relatively poor. As in the case of the Chinese examples, Slovenian terraces recognition might still benefit from the inclusion of additional data, e.g. Landsat or Sentinel imagery or other commercial satellite imagery with a higher resolution, but the main goal was to test deep learning capabilities exclusively on DEM data due to the rather high forest cover in Slovenia (according to the Slovenia Forest Service, 58% of the country is covered with forests).

Some natural and artificial phenomena are similar to cultivated terraces and make the recognition more difficult. Since terraced landscapes are located in places where apparent patterns of two or more terraced surfaces appear (Berčič, 2016), it was not surprising that we encountered natural or other artificial terrace-like forms during the (mis)recognition. Natural terraces appear as step-like landforms resembling terraces, formed by natural processes (Kladnik et al., 2017a; see also Del Val et al., 2015; Ferk, 2016). In our case, some specific features were recognised as terraces (e.g. foothills). In contrast, there were many more examples of falsely recognised terraces associated with anthropogenic elements, such as roads and railway lines (see Fig. 9). We noticed that some slopes with road cuts can be recognised as terraces. According to a formal description, these can also be considered terraces, but they are not cultivated. The span of such a 'terrace' varies and there is no clear repeating pattern. Therefore, the solution could be to define the span of terraces more strictly and the minimum number of terraced surfaces in one terraced area. By including remote sensing imagery, roads can be excluded based on the spectral response for certain surface materials (asphalt, gravel).

Terraces generally share similar spatial texture characteristics (Zhao et al., 2021), whereas natural landscape types influence the shape and distribution of cultivated terraces to some extent (Berčič, 2016). Our analysis included different landscape types across Slovenia, where different geomorphic processes as well as anthropogenic influences are present (Zorn et al., 2020). These processes have left a characteristic imprint on the landscape, which means that cultivated terraces may differ from one area to another and therefore different recognition issues may arise regarding the success of modelling. In our case (Tab. 5, Fig. 7), the highest Jaccard index was observed in the Mediterranean hills (in the west) and the Pannonian hills (in the east), where terraces with vineyards are common (Ažman Momirski, 2019). The reasons for the higher success rate in these regions could be that the terraces in these areas have the most pronounced shape and are well maintained and less overgrown. Therefore, they are clearly visible for human and deep learning recognition. In such areas, Lidar scanning of the ground is also more detailed with a higher density of ground points. Namely, data collection is easier due to plants (vines) growing in a row with some empty space all around, so the Lidar scanning can easily reach the ground. Based on the geometric characteristics of the terraces (which are usually more than 2 m wide; Drobnjak, 1989), we consider the 1m Lidar data to be sufficient and not the reason for the discrepancies. Terraces are most often covered with grasslands (as shown in Tab. 5). This is not surprising, because land abandonment and overgrowth of agricultural areas (fields) is very common in Slovenian peripheral areas (Gabrovec & Kumer, 2019), especially in the Dinaric Alps. The higher share of terraces recognised by deep learning is also related to arable land, which might also be the result of some misrecognised areas (see 4.2.2).

The advantage of deep learning is the modularity of the model architectures, which can be quickly adapted to new tasks. The convolutional neural networks we have used are very well suited for processing spatial data and remote sensing (Yuan et al., 2021), as they can efficiently model high-order dependencies in the local area. On the other hand, deep models require a large amount of data. In remote sensing applications, the sheer quantity is usually not a problem, but ensuring sufficient quality often is. Some features of interest may be missing in the training data. Moreover, labelled features rarely follow the exact boundary in the underlying raster, as human annotators are influenced by various factors and are seldom completely focused on their visual interpretation. Some objects are also complex to digitise (Van Coillie et al., 2014). Still, the main source of noise in our case is the absence of labels of overgrown terraces (Kladnik et al., 2016b; Glušič et al., 2021). As we observed in our case, the training procedure of deep models that considers several samples in a single step is surprisingly robust. This has been demonstrated by comparing our model's predictions to the testing labels (see 4.1).

There are more ways to further mitigate the problem of noise by considering additional data sources and domain knowledge. Since there are many features with terraces-like shape in the Lidar DEM data (e.g. winding roads, river terraces), the rate of falsely classified terraced areas could be reduced by including aerial orthophotos or other multispectral remote sensing images. Lu et al. (2023), refined the recognition results, obtained using deep learning on optical imagery using slope information and exclude areas with low levels of slope (e.g. less than 2°). The analysis of optical remote sensing images (e.g. aerial or satellite multispectral images) could help us in our case to exclude certain non-vegetated areas (such as roads covered with asphalt or stone quarries), but this approach solely cannot adequately improve capturing terraced areas with indistinct terrace banks and abandoned, overgrown cultivated terraces (Kladnik et al., 2016b). To provide solid morphological information, using Lidar data is therefore unavoidable in such cases and other data sources may only provide auxiliary information.

Looking at the specific failure cases of our model (see Fig. 9) we acknowledge the fact that the diversity of terraces and their similarity to other landscape features should be additionally investigated. A clear division between similar, terraces-like features could be promoted during training using similar landscape features. Such features might include a winding road, a railway line, or a road embankment, etc. and could be obtained from different sources (e.g. land use). The model may also lose sensitivity to some landscape properties due to our data encoding using DEM derivatives. This choice allows the model to focus on small changes in the landscape but makes it difficult to reconstruct coarser properties. The addition of a less detailed (generalized) DEM (e.g. averaged Lidar DEM) may help to provide more information about the general slope of the area and to exclude flat areas, where, for example, terraces-like pattern can be seen in the ploughed fields.

It is important to remember that our study only evaluates the capabilities of a deep learning model and does not consider manual pre- or post-processing, which can upgrade our approach. Despite the limitations of the presented model, we believe that computer analyses of digital elevation models are needed for successful construction and maintenance of terraces registers, especially in countries like Slovenia, where most of the land is covered by forests. In such scenarios, fieldwork is limited by potentially poor accessibility as well as time and financial constraints (Berčič, 2016). A more robust model, stemming from our work, could quickly and cost-effectively map abandoned and overgrown terraces to promote their potential revitalisation (Sakellariou et al., 2021).

Beyond terraces, other relief features could be tested for recognition possibilities with deep learning methods, for example dolines and collapsed dolines (e.g. Ciglič et al., 2022; Mihevc & Mihevc, 2021), denuded caves (Grlj & Grigillo, 2014), fluvial terraces (Wei et al., 2017), landslides (Verbovšek et al., 2019), alluvial fans (Norini et al., 2016), dunes (Mohamed & Verstraeten, 2012), and glacially reshaped landforms (Chandler et al., 2018). Despite the increasing availability of objective methods, manual mapping is still used to refine extracted features, e.g. fluvial terraces (Gardner et al., 2020). Deep learning is still underutilised in several geographical sub-fields, e.g. geomorphology and geomorphometry. Rare examples of the use of automated analysis include the analysis for categorising different rock types (Patel & Chatterjee, 2016), recognising dolines (Mihevc & Mihevc, 2021), and other geomorphic features (Maxwell et al., 2023).

6. Conclusions

Terraced landscapes are the result of human adaptation to nature, mainly for the purposes of improving the conditions for agriculture. Nowadays, many terraces are being abandoned, but if the need were to arise for their revitalisation (e.g. due to food shortages), it is important to know the locations of existing and abandoned terraces. In this work, we tested the possibilities for recognising terraces using a U-Net deep learning architecture and Lidar DEM. Unlike past studies, we did not use satellite or aerial multispectral imagery for the deep learning process. We found that the recognition of cultivated terraces solely with the Lidar DEM is possible. During the testing phase, the method showed robustness to the input training data, which is encouraging for further studies and improvement. Comparing the modelled layer and the layer of cultivated terraces, the register showed an overall accuracy of 85%, but the kappa index was only 0.22. A detailed inspection showed that the recognition was most successful in areas with pronounced terraces (e.g. the Mediterranean parts of Slovenia). Our results did not contain any post-processing and are generally not yet suitable for direct application, as there were quite a number of errors. However, our analysis was able to highlight a number of challenges (potential false recognition issues) that need to be considered when defining training datasets.

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