Landslide Susceptibility Prediction from Satellite Data through an Intelligent System based on Deep Learning

Alessandro Giuseppi[1], Leonardo Pio Lo Porto[1], Andrea Wrona[1] and Danilo Menegatti[1,*]

***Abstract*— Landslides are critical natural hazards whose frequency and severity are increasing due to climate change and human activities. The consequences of landslides are severe and can lead to the destruction of homes, infrastructures and the contamination of water supplies, with severe impact also on the local ecosystems and the disruption of natural habitats. This article examines the application of an ad-hoc neural network-based intelligent system to evaluate the landslide susceptibility of the terrain on the basis of satellite data. The proposed system is validated on data from Lombardia and Abruzzo, two Italian regions that have been particularly subject to the landslide phenomenon. Results indicate that the CNN model is able to correctly identify landslide occurrences with high accuracy, demonstrating that CNNs are capable of providing accurate susceptibility mapping at a local scale and surpassing the performance of existing solutions available in the literature.**

I. INTRODUCTION

Landslides are natural disasters which cause significant economic losses, property damage and human casualties. According to the reports provided by the Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA) [1], with more than 620,000 landslides, Italy is one of the European nations most impacted by the landslide phenomenon, with an affected area of about 24,000 km^2, equivalent to about 7.9 percent of the national territory. Numerous studies focused on the study of past landslide phenomena and soil structures to identify Landslide Susceptibility Maps (LSMs), typically employing one of three main methodologies: expert-based, physical-based, and statistical methods. In particular, physical-based techniques simulate the stability of a downhill given its physical characteristics such as geological rock and soil conditions and compute the equilibrium between destabilizing variables and slope strength, whereas expert-based techniques rely mostly on the qualitative opinion of a domain expert [2].

In recent years, with the advancement of artificial intelligence and the development of new techniques in the Machine Learning (ML) domain, statistical models have become the focus of many researchers, becoming one of the most popular tools for studying landslide phenomena. Statistical methods are based on the analysis of past events correlating it with influencing factors like slope, land cover and vegetation.

[1] Department of Computer, Control and Management Engineering "Antonio Ruberti" of the University of Rome Sapienza, Via Ariosto 25, 00185, Rome, Italy.

This study has been partially supported by the project "Intelligent Control Systems: Analysis, Design and Applications " of the University of Rome "La Sapienza", protocol n. RP1221816BE0C9AB

* Corresponding author: menegatti@diag.uniroma1.it

This paper seeks to explore the potential of convolutional neural networks (CNNs) [3], [4], [5] for landslide susceptibility assessment at a large scale, proposing an ad-hoc design that aims at improving the performance attained by existing solutions.

The main contributions of this study are:

- The design of a customized deep convolutional network to evaluate landslides susceptibility maps reliant only on satellite data, enabling a seamless analysis that requires minimal expert supervision;
- The validation of the proposed solution on real data from two Italian regions.

The remainder of the paper is structured as follows: Section II reports an overview of the related works; Section III describes the satellite data sources and products used in this study; Section IV outlines the dataset considered and the designed neural network architecture; Section V reports the results of the test conducted on data from the Italian regions of Lombardia and Abruzzo, while Section VI draws the conclusions and highlights future works.

II. RELATED WORKS

Various studies have demonstrated the effectiveness of machine learning and deep neural networks for the evaluation of various safety-related risk factors, such as fire risk [6], [7] and landslide susceptibility [8], [9]. For instance, logistic regression was used by numerous researchers as the authors of [8] to show how, by considering influencing factors like slope, lithology, land cover, aspect, hill-shade, it is possible to evaluate LSMs in various regions such as China [9] and Sri Lanka [10]. The authors of [11] combined logistic regression with a technique called frequency ratio, which consists of a statistical method used to assess the relative risk of landslides by using the ratio of the frequency of landslides in areas with certain characteristics (e.g., slope, land use, soil type) to the frequency of landslides in areas without those characteristics. This ratio provides a relative measure of risk that can be used to better understand and reduce the risk of landslides in a given area. The work [12] illustrates different results from the use of a classical logistic regression approach and deep neural networks (DNNs) concluding that the latter approach performs better and is capable of more general results, highlighting the benefit of more powerful ML models in solving the task.

In this direction, decision trees and random forests, which are among the most popular ML models, were used in [13], [14] to assess landslide risk in the Turkish region and in the Metropolitan City of Istanbul. Nowadays, the literature focuses mostly on new methods from the deep learning domain, such as Recurrent (RNNs) and Convolutional Neural Networks (CNNs) that envisage a custom architecture tailored for signal and image analysis [5].

The work [15] describes the general deep learning approach used to face the topic of landslide susceptibility assessment using DNNs. One of the first studies to investigate DNNs for estimating a landslide probability map was [16], in which a DNN was fed with high-resolution images taken from a LiDAR (light detection and ranging) camera in order to compute a Digital Elevation Model (DEM) and some derivative factors. In [17] and [18] DNNs are used, in combination with a GIS program, to predict a landslide susceptibility map of respectively the Riomaggiore area and Langat River Basin in Malesya. [19] makes a comparison on the performance obtained in computing LSM among a feed-forward neural network, a RNN and a 1-dimensional CNN. As an improvement of the previous work, the authors of [3] illustrate how to use a CNN in the context of landslides hazard and they present three different kinds of representation of the data in 1 to 3 dimensions. The present paper focuses on a particular CNN architecture, known as U-NET [4], which has become widely used in recent years for numerous studies in the biomedical field and other areas related to image analytics, such as satellite products.

III. Landslide influencing factors description and data acquisition

This section provides a general description of the satellite products used for this study, as well as the main software solutions employed for their management.

A. Geographic Information System Mapping

A geographic information system (GIS) is a computer program that collects, stores, verifies, and presents information about spatial data on the earth surface [20]. All the images passed through these kind of system are georeferenced, meaning that they carry information regarding their spatial coordinates to be displayed and analysed in a specified coordinate system, such as the standard World Geodetic System 1984 (WGS84). Having fixed a coordinate systems, it is possible to combine several different information and satellite products, such as land surface temperature, streets, vegetation, soil features, by stacking multiple different image layers one over the other. For this study the open-source software Quantum GIS (QGIS), depicted in Figure 1 was used, to extract and manage data from various public sources detailed in the following.

B. Satellite imaging sources

The LandSat-8 and TERRA satellites are the two main sources considered for this work. TERRA is a satellite platform capable of providing various measurements thanks to its five onboard sensors, namely:

- **ASTER** (Advanced Spaceborne Thermal Emission and Reflection Radiometer)
- **CERES** (Clouds and Earth's Radiant Energy System)
- **MISR** (Multi-angle Imaging SpectroRadiometer)
- **MODIS** (Moderate-resolution Imaging Spectroradiometer)
- **MOPITT** (Measurements of Pollution in the Troposphere)

For this study, we considered mainly data gathered by the ASTER and MODIS sensors.

The analysis of this work will be based on the following 10 satellite features, to be passed to the CNN: Digital Elevation Model (DEM), slope, aspect, profile curvature, tangential curvature, land cover, lithology, Normalized Difference Vegetation Index (NDVI), Topographic Wetness Index (TWI), soil type. The following subsection will detail each of the considered satellite products and their sources.

*1) **DIGITAL ELEVATION MODEL (DEM)**:* A Digital Elevation Model (DEM) is a three-dimensional representation of the earth's surface, that was derived from a variety of sources, including satellite imagery, airborne LiDAR, Global Positioning System (GPS), airborne photography, and ground surveys. In this study, DEM was taken from the product ASTER Global Digital Elevation Model (GDEM) V003 [21], which is characterized by a resolution of 30 meters per pixel. Figure 2 shows the DEM of the Italian region of Abruzzo.

*2) **SLOPE**:* Slope factor is a measure of the steepness of a mountain and in general terrain. It is typically expressed as a ratio of the height of the mountain divided by its horizontal extension [22]. Slope can be easily derived from the DEM by automated tools, and represents one of the most crucial factor inflencing the severity and extension of a landslide. Figure 3 shows the slope map computed using the QGIS "Slope" tool.

*3) **ASPECT**:* Aspect is another measure that can be derived from the DEM and describes the direction a surface or line is facing, usually measured in degrees from the North. It is an important factor in many GIS analyses and it can be used to describe the orientation of a surface, typically a hillside. Aspect can also be used to determine the potential for erosion, a critical factor for landslides, as areas with a steeper slope and a southern or western aspect are more prone to erosion than areas with a flatter slope and a northern or eastern aspect [23]. Figure 4 shows the aspect map computed using QGIS.

*4) **PROFILE CURVATURE**:* A mountain's profile curvature is a measure of its shape and is expressed as a combination of its steepness, convexity, and concavity. Steepness describes how inclined is the mountain, convexity is the degree to which the mountain's profile rises from its base and concavity is the degree to which it sinks from its peak. Landslides are more likely to occur on slopes with higher profile curvature because the steeper gradients and convex curvatures create a shallow angle of repose, making it easier for the material to move down-slope. Figure 5 shows the map computed by QGIS starting from the DEM.

*5) **TANGENTIAL CURVATURE**:* Tangential curvature in GIS analysis is used to measure the amount of curvature along a line or polygon. It affects the amount of stress a slope experiences, as, the higher the tangential curvature, the

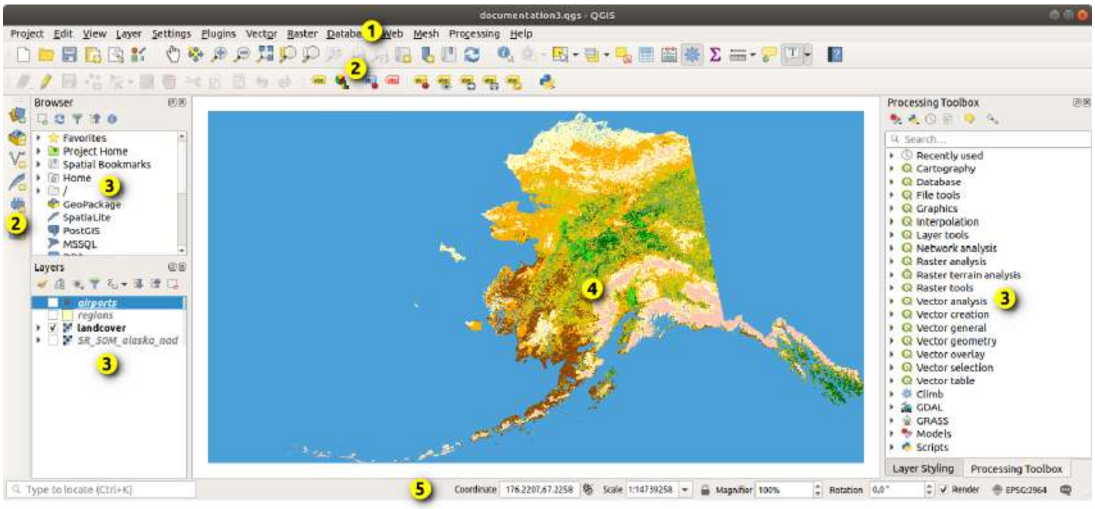

Fig. 1. QGIS interface. At the top it is present a Menu Bar (1); just below the toolbar (2); on the left and on the right we can find the panels (3) where we have the file browser on the top left, on the bottom left the layers uploaded on QGIS project and on the right the processing toolbox; at the center we have the map view (4) and the bottom the status bar (5)

Fig. 2. Digital Elevation Model of Abruzzo

Fig. 3. Slope Abruzzo computed from QGIS

greater the force that is applied to the slope. Additionally, tangential curvature can cause water to gather in certain areas, making the slope more vulnerable to landslides and soil erosion. In Figure 6 we report a map representation of the Abruzzo tangential curvature.

*6) **TOPOGRAPHIC WETNESS INDEX (TWI)**:* Topographic wetness index (TWI) is an index that incorporates both topographic slope and the drainage area of a given point on a landscape. It is used to quantify the amount of water that a given location can hold and is a useful tool for understanding the hydrological conditions of a particular area. TWI is used to identify wetter areas in a landscape that are likely to have higher levels of soil moisture and therefore be more vulnerable to runoff and erosion. TWI can provide useful information for landslide risk assessment, as areas with higher TWI values are more likely to experience landslides due to the increased saturation of the soil. Figure 7 shows the TWI of the Abruzzo region evaluated by QGIS from the DEM of the area.

*7) **NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI)**:* The Normalized Difference Vegetation Index (NDVI) is a normalized index used to measure the greenness /amount of vegetation over large areas and it is used to identify healthy vegetation. The NDVI is calculated using the difference between two types of reflected radiation, typically visible and near-infrared radiation. Vegetation absorbs visible light and reflects near-infrared light, while the reverse is true for soil and other non-vegetation surfaces. NDVI is calculated by subtracting the near-infrared (NIR) band from the visible red (Red) band in an image, and then dividing the result by the sum of the two bands as per the equation below:

$$NDVI = \frac{(REF_{nir} - REF_{red})}{(REF_{nir} + REF_{red})} \tag{1}$$

The resulting value ranges between -1 and +1, with higher values indicating vegetation presence due to the fact the more vegetative is the plant the higher is the value of its NIR

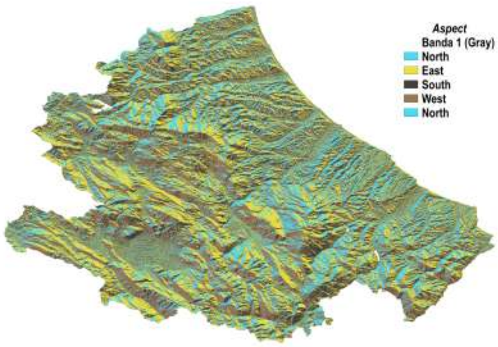

Fig. 4. Aspect Abruzzo computed by QGIS.

Fig. 5. Profile curvature Abruzzo computed by QGIS

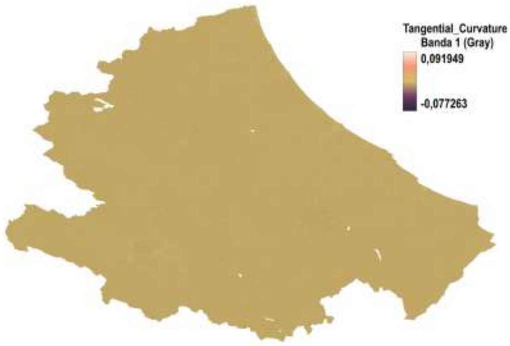

Fig. 6. Tangential curvature of Abruzzo computed by QGIS

Fig. 7. Topographic Wetness Index of Abruzzo

reflectance. Values between -1 and 0 represents dead plants or inanimate objects, as not cultivated fields or water basins. NDVI is an important factor to consider in the study of LSM, as the lack of vegetation can be an indicator of weak or unstable ground. NDVI is typically measured using satellite imagery. For our project Landsat-8 was used, as depicted in Figure 8.

*8) **LITHOLOGY**:* Lithology is the basis for understanding the origin of a region's sedimentary, metamorphic, and igneous rocks. The lithology of a particular area can be an important factor in determining the likelihood of a landslide occurring, as different rock types have different levels of stability and resistance to erosion, porosity and permeability. For example, in areas with sedimentary rocks, the presence of weak layers of shale and clay can increase the risk of landslide activity. Conversely, areas with more resistant metamorphic or igneous rocks may be less susceptible to landslides. The European Soil Data Center (ESDAC) was the source of the data employed in this study, which used the European Landslide Susceptibility Map version 2 (ELSUS v2) [24] to obtain the data reported in Figure 9.

*9) **SOIL TYPE**:* Soil type refers to the physical and chemical characteristics of a given soil. These characteristics include texture, structure, color, acidity, fertility, and drainage. Soil types vary based on the amount of mineral, organic, and humus content, as well as the level of clay, silt, sand, and other inorganic particles contained within it. In our study soil type was taken from the "Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria" (CREA) [25] and is reported in Figure 10.

*10) **LAND COVER**:* Land cover is a satellite product that refers to the physical characteristics of the land and its vegetation, such as soil type, tree species, and other vegetation. Land cover data was acquired from the ELSUS v2 auxiliary dataset [24] as was done for the lithoglogy. The land cover class names were taken from ESA GlobCover2009 data [26]. Figure 11 shows the map processed with QGIS with the corresponding legend.

*11) **LANDSLIDES MASK**:* The final satellite product considered in this study is related to historic data on landslides occurred in the past decades. For the purpose of this study, this information is not provided as input to the CNN and instead is used for its training as a target value for its LSM predictions. The masks were obtained from the idroGEO platform [27] [28] which is an Italian platform on hydro-geological instability. Figure 12 shows the data as imported in QGIS.

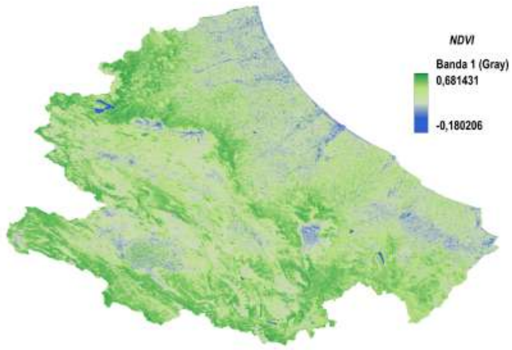

Fig. 8. Normalized Difference Vegetation Index of Abruzzo

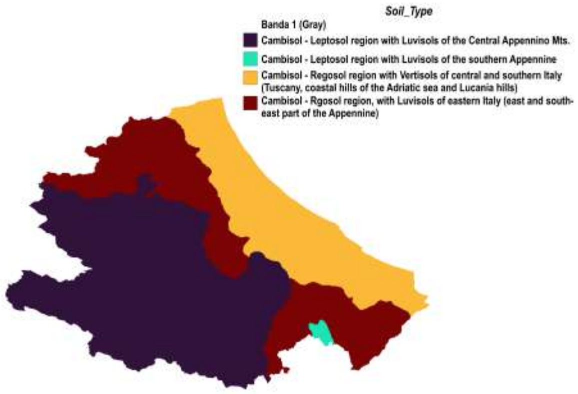

Fig. 10. Soil Type of Abruzzo.

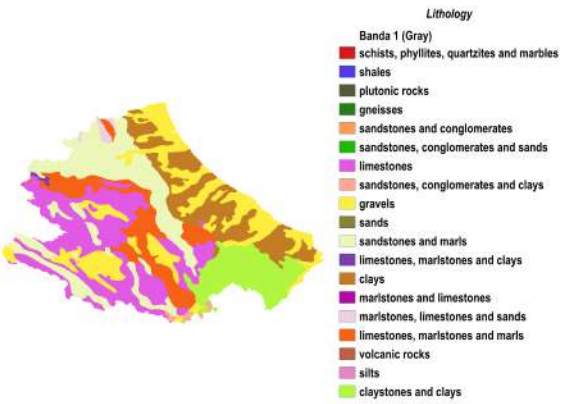

Fig. 9. Lithology of Abruzzo.

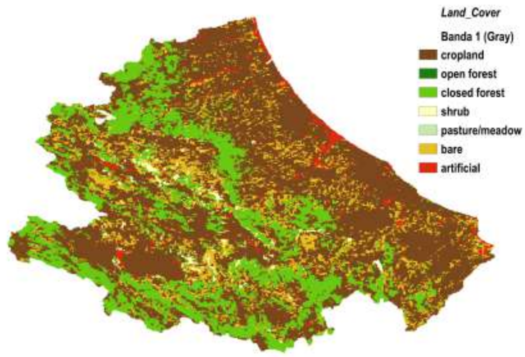

Fig. 11. Land Cover of Abruzzo.

IV. Neural Network design and dataset specification

A. Dataset creation

After acquiring satellite images and data from the various sources and satellite platforms and creating layers of the respective factors using QGIS, Python was used as a programming language to perform some pre-processing operations in order to better prepare the dataset for the learning process. The collected data had to be re-projected to a common coordinate reference system (CRS) and resized to a common dimension, as the resolution of the various products was not always equivalent. After stacking the 10 different images described in the previous section, the area was divided into smaller patches of 256x256 pixels with an overlap of 64 pixels. We mention that the resulting stacks are equivalent to 256×256 images with 10 different channel. The landslide masks were also correspondingly divided, so that each stack of 10 images was associated with a mask of the same area.

In order to balance the training dataset, it was decided to filter out the area in which the landslide mask reported a percentage of landslides lower than 0.04%. The dataset was hence randomly partitioned in 80% training data and 20% testing data, avoiding any overlapping between the two sets, and then augmented by performing rotations of 90°, 180° and 270° and both horizontal and vertical flips. For this study, we conducted the training process of the DNN over two separate datasets, covering respectively the Italian regions of Lombardia and Abruzzo.

B. Deep Neural Network architecture

The U-NET is a convolutional neural network architecture, originally proposed in [4], that was particularly tailored for image segmentation tasks. At its core, U-NET is a CNN with a specialized layer architecture, known as the encoder-decoder, in which the input image is first *encoded* by passing through a series of convolutional layers, and then *decoded* by a series of up-sampling layers (Figure 13). In the encoder portion of the network, the nonlinear convolutional layers perform a form of feature extraction, while in the decoder part the extracted features are analysed to extract the target information, which typically is displayed in the form of an image (in our case a LSM). The "U" shape of the network derives from the presence of some *skip-connections* that forward information from a layer in the encoder to its corresponding layer in the decoder, allowing the network to capture both low-level and high-level features

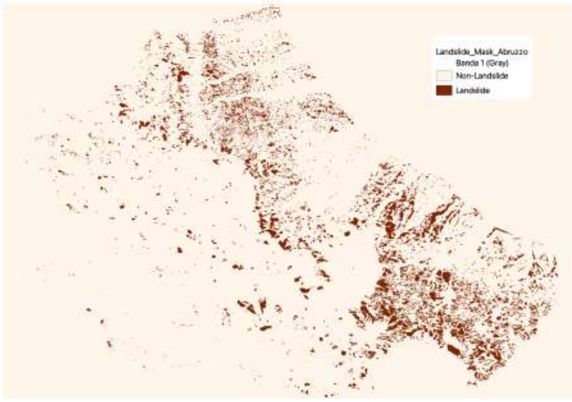

Fig. 12. Landslide mask Abruzzo; Red pixels represent the presence of a landslide in the corresponding area.

and correlations, making the U-NET an ideal choice for localisation and segmentation tasks.

In order to obtain more satisfactory results and reduce overfitting, some regularisation actions were included in our architecture by adding dropout and batch normalisation layers. The resulting architecture is reported in Figure 13 and includes 23 convolutional layers.

As mentioned, the U-NET output consists of an image, and for our task, we encoded in each of its pixels, through the sigmoid activation function of the final layer, a value between 0 and 1 representing the confidence of the corresponding area being subject to landslide risk. The resulting output image is then a 256×256 heatmap capturing a distribution of the landslide susceptibility of the considered area.

The loss function, which is a fundamental part of the design of any ML tool as it defines the training objective, was chosen to be a Weighted Binary Crossentropy (WBCE) evaluated by comparing the individual pixels predicted by the CNN against the landslide mask. We set a weight 15 times greater to the pixels encoding a high landslide risk (i.e., whose value on the landslide mask was equal to 1) so that the CNN training does not suffer from the abundance of 0 values in its target labels.

Denoting the 256×256×10 stack of input images as x, the resulting WBCE loss takes the form:

$$L(x) = -\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{W_i^1} \cdot y_i \log \hat{y}_i(x) + \boldsymbol{W_i^0} \cdot (1-y_i)\log(1-\hat{y}_i(x)) \tag{2}$$

Where W_i^0 and W_i^1 represent respectively the weights given to the classes 0 (low level of landslide susceptibility) and 1 (high value of susceptibility), N is the number of pixels in the output image, y_i is the ground truth label for pixel i, and $\hat{y}_i(x)$ is the susceptibility value predicted by the model for the same pixel.

As a performance metric to evaluate the performances of the neural network we used the AUROC curve (Area Under the Receiver Operating Characteristic Curve). The Area under Curve (AUC) value is used to measure the performance of a binary classifier and is evaluated by integrating the curve that reports the true positive rates against the false positive rates predicted by the classifier. The higher the AUC value, the better the performance of the CNN in terms of discerning correctly the two classes.

V. Case Study

A. Areas of interests

The area of interests considered in the project are two Italian region, Lombardia and Abruzzo, two regions characterized by signifcant landslide phenomena over the past decades. In particular, Lombardia is a region in northern Italy that is prone to landslides due to its mountainous terrain, steep slopes, and frequent seismic activity [29], while Abruzzo is known for having a high density of unstable rock formations and high levels of precipitation, which combined make it an area susceptible to landslides [30], [31]

B. Results

The model was trained with a Tesla T4 over 200 epochs, using a batch size of 16 and a learning rate of 0.001. An early stopping procedure was introduced to avoid overfitting during the training. Table I summarizes the setting used in the implemented convolutional neural network.

In Figure 14 it is possible to observe the predicted output of the neural network and the ground truth compared of two patches of the Lombardy region.

As it can be seen from the two proposed figures, the prediction of the image is very accurate, with the neural network able to identify the points that are subject to the highest landslides risk precisely. It can also be seen that the neural network does not only classify as susceptible to landslides risk the points where the landslide actually occurred, but also their neighboring areas, thus displaying on the map critical zones around unstable terrain where a landslide has occurred in the past.

In Fig. 15 and Fig. 16 are respectively represented the evolution of the loss function over the epochs and the AUC performance metric. After 175 epochs it can be seen that the network starts to overfit, so the early stopping procedure implemented stops the training at 200 epochs.

The results obtained are also highlighted by the AUROC metric (see Figure 16) that shows how the neural network is able to correctly classify the critical areas over the test dataset, as the AUC reaches a value of about 0.98 after 175 epochs, improving the results obtained by other neural-network based systems [3] or [19].

TABLE I
U-NET SETTINGS.
BS, LR AND BN REPRESENT RESPECTIVELY THE BATCH SIZE, LEARNING RATE AND BATCH NORMALIZATION HYPER PARAMETERS

Optimizer	Epochs	BS	LR	BN	Dropout
Adam	200	16	0.001	0.8	0.8-0.2

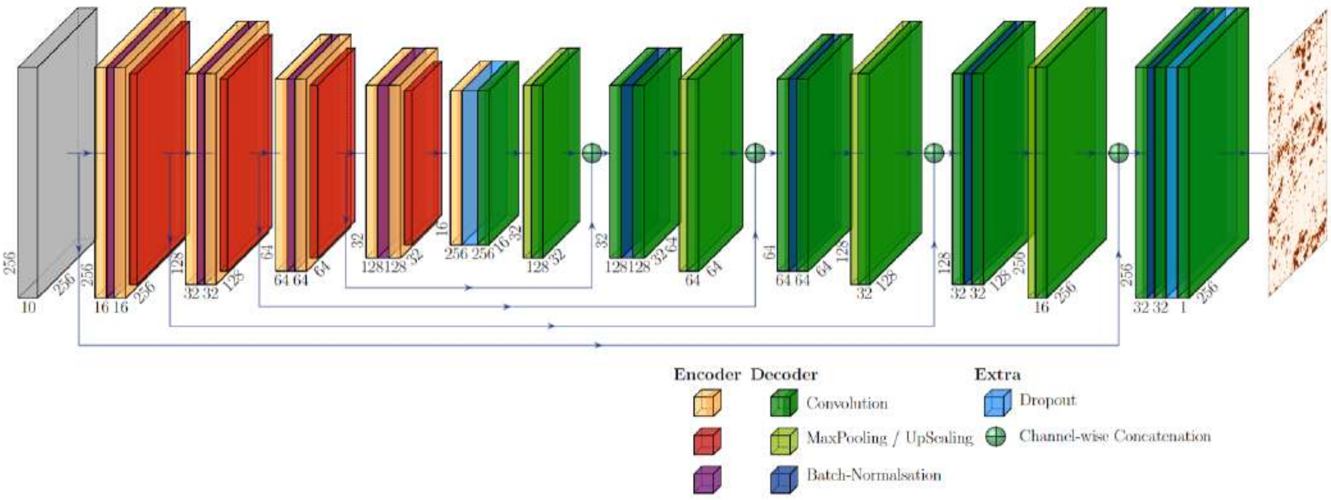

Fig. 13. The U-NET architecture employed in this study, divided into the encoder, or "contractive path" (left), and the decoder, or "expansive path" (right) parts.

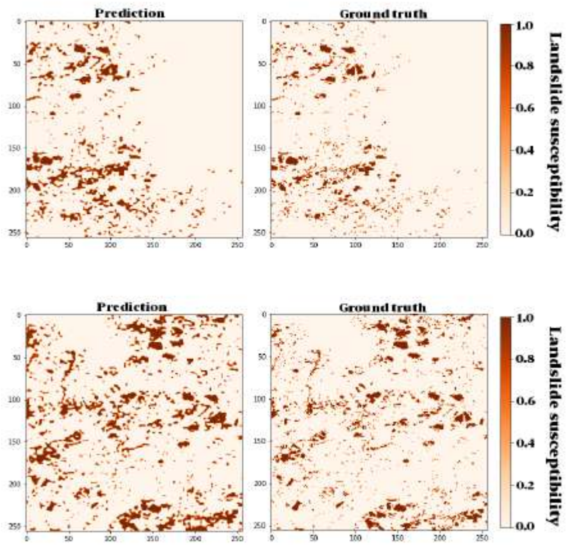

Fig. 14. Comparison between predicted image (on the left) and the ground thruth (on the right) of a Lombardy zone

For the sake of completeness, and to further stress the generalization capabilities of the proposed model, we also report the results obtained by testing the neural network on the Abruzzo region. Figure 17 shows that the results are in line with the previous case, with the predicted critical areas slightly less defined with respect to the previous case probably due to the more complex lithology of the region.

VI. Conclusions and Future Works

Landslides are a major natural hazard whose severity is increasing due to climate change, deforestation and poorly regulated construction activities. This paper, proposed a neural network-based system to identify landslide-prone areas using satellite data. Several landslide influencing factors were considered, such as slope, aspect, lithology and land cover type. The performance of the developed system was evaluated using the ROC curve, leading satisfactory results that attain higher performance compared to existing solutions. A possible future work is related to the inclusion of more influencing factors to improve the predictions, including also ground data gathered by an IoT sensor network.

VII. Acknowledgments

The authors acknowledge the members of the ESA project ARIES (grant agreement No 4000133127) and in particular engineer Cristiano Cialone for the fruitful discussions and support.

References

[1] A. Trigila, C. Iadanza, B. Lastoria, M. Bussettini, and A. Barbano, "Dissesto idrogeologico in italia: pericolosità ed indicatori di rischio," 2021.

[2] F. Guzzetti, M. Manunta, F. Ardizzone, A. Pepe, M. Cardinali, G. Zeni, R. Paola, and R. Lanari, "Analysis of ground deformation detected using the sbas-dinsar technique in umbria, central italy," *Pure and Applied Geophysics*, vol. 166, pp. 1425–1459, 09 2009.

[3] Y. Wang, Z. Fang, and H. Hong, "Comparison of convolutional neural networks for landslide susceptibility mapping in yanshan county, china," *Science of The Total Environment*, vol. 666, pp. 975–993, 05 2019.

[4] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Lecture Notes in Computer Science*, pp. 234–241, Springer International Publishing, 2015.

[5] F. D. Priscoli, A. Giuseppi, and F. Lisi, "Automatic transportation mode recognition on smartphone data based on deep neural networks," *Sensors*, vol. 20, p. 7228, Dec. 2020.

[6] A. Santopaolo, S. S. Saif, A. Pietrabissa, and A. Giuseppi, "Forest fire risk prediction from satellite data with convolutional neural networks," in *2021 29th Mediterranean Conference on Control and Automation (MED)*, IEEE, June 2021.

[7] A. Giuseppi, R. Germanà, F. Fiorini, F. D. Priscoli, and A. Pietrabissa, "UAV patrolling for wildfire monitoring by a dynamic voronoi tessellation on satellite data," *Drones*, vol. 5, p. 130, Nov. 2021.

[8] X. Sun, J. Chen, Y. Bao, X. Han, J. Zhan, and W. Peng, "Landslide susceptibility mapping using logistic regression analysis along the jinsha river and its tributaries close to derong and deqin county, southwestern china," *ISPRS International Journal of Geo-Information*, vol. 7, no. 11, 2018.

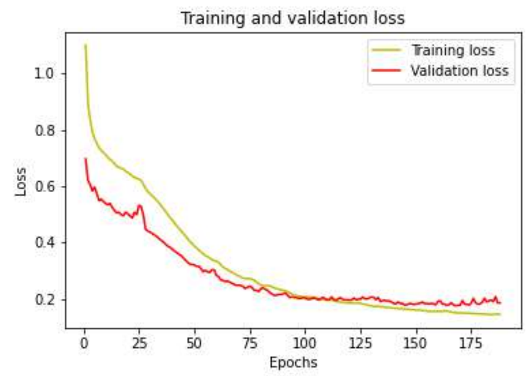

Fig. 15. Evolution of the Weighted Binary Cross Entropy loss function along epochs of Lombardy region

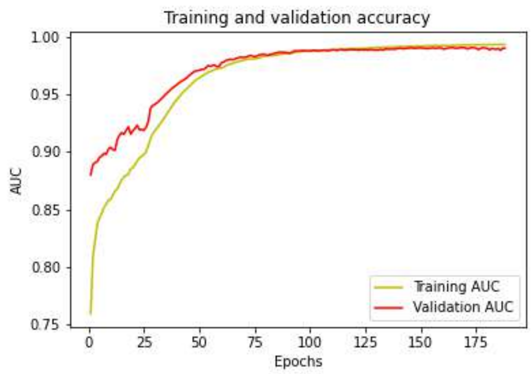

Fig. 16. Evolution of the overall ROC curve along epochs of Lombardy region

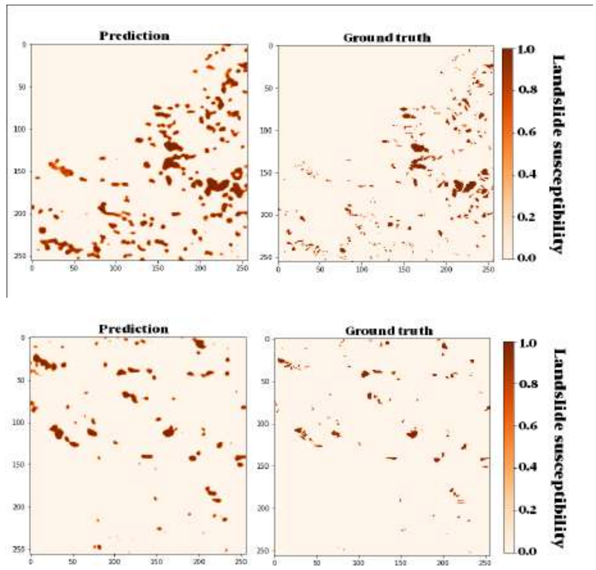

Fig. 17. Comparison between predicted image (on the left) and the ground truth (on the right) of an Abruzzo zone

[9] C. Xu, W. Zhang, Y. Yi, and Q. Xu, *Landslide Susceptibility Mapping Using Logistic Regression Model Based On Information Value for the Region Along China-Thailand Railway from Saraburi To Sikhio, Thailand*. IEEE, July 2019.

[10] H. Hemasinghe, R. Rangali, N. Deshapriya, and L. Samarakoon, “Landslide susceptibility mapping using logistic regression model (a case study in badulla district, sri lanka),” *Procedia Engineering*, vol. 212, pp. 1046–1053, 2018. 7th International Conference on Building Resilience: Using scientific knowledge to inform policy and practice in disaster risk reduction.

[11] F. Mahadadi and A. Boumezbeur, “Landslide susceptibility mapping using logistic regression and frequency ratio approaches, case study from souk ahras region, n e algeria,” *Italian Journal of Engineering Geology and Environment*, vol. 1, pp. 45–53, 2020.

[12] H. Nefeslioglu, C. Gokceoglu, and H. Sonmez, “An assessment on the use of logistic regression and artificial neural networks with different sampling strategies for the preparation of landslide susceptibility maps,” *Engineering Geology*, vol. 97, pp. 171–191, 04 2008.

[13] H. Nefeslioglu, E. Sezer, C. Gokceoglu, A. Bozkir, and T. Duman, “Assessment of landslide susceptibility by decision trees in the metropolitan area of istanbul, turkey,” *Mathematical Problems in Engineering*, vol. 2010, 01 2010.

[14] H. Akinci, C. Kilicoglu, and S. Dogan, “Random forest-based landslide susceptibility mapping in coastal regions of artvin, turkey,” *ISPRS International Journal of Geo-Information*, vol. 9, no. 9, 2020.

[15] Z. Ma and G. Mei, “Deep learning for geological hazards analysis: Data, models, applications, and opportunities,” *Earth-Science Reviews*, vol. 223, pp. 1–33, 12 2021.

[16] P. Gorsevski, M. Brown, K. Panter, C. Onasch, S. M. Anita, and J. Snyder, “Landslide detection and susceptibility mapping using lidar and an artificial neural network approach: a case study in the cuyahoga valley national park, ohio,” *Landslides*, vol. 13, 05 2015.

[17] L. Ermini, F. Catani, and N. Casagli, “"artificial neural networks applied to landslide" "susceptibility assessment",” *Geomorphology*, vol. 66, pp. 327–343, 03 2005.

[18] S. N. Selamat, N. A. Majid, M. R. Taha, and A. Osman, “Landslide susceptibility model using artificial neural network (ann) approach in langat river basin, selangor, malaysia,” *Land*, vol. 11, no. 6, 2022.

[19] Y. Yi, W. Zhang, X. Xu, Z. Zhang, and X. Wu, “Evaluation of neural network models for landslide susceptibility assessment,” *International Journal of Digital Earth*, vol. 15, no. 1, pp. 934–953, 2022.

[20] E. Ali, “Geographic information system (gis): definition, development, applications & components,” *Department of Geography, Ananda Chandra College.*, 2020.

[21] NASA/METI/AIST/Japan Spacesystems And U.S./Japan ASTER Science Team, “Aster global digital elevation model netcdf v003.” https://lpdaac.usgs.gov/products/astgtmv003/, 2019.

[22] M. Dunn and R. Hickey, “The effect of slope algorithms on slope estimates within a GIS,” June 1998.

[23] P. Guth and M. Kane, “Slope, aspect, and hillshade algorithms for non-square digital elevation models,” *Transactions in GIS*, vol. 25, pp. 2309–2332, Oct. 2021.

[24] European Soil Data Center (ESDAC), “European landslide susceptibility map version 2 (elsus v2).” https://esdac.jrc.ec.europa.eu/content/european-landslide-susceptibility-map-elsus-v2.

[25] Consiglio per la ricerca in agricoltura e l’analisi dell’economia agraria (CREA), “Soil layers.” https://soilmaps.wordpress.com.

[26] S. Bontemps, P. Defourny, E. Van Bogaert, O. Arino, V. Kalogirou, and J. R. Pere, “Products description and validation report,” 2011.

[27] ISPRA - Regione Abruzzo, “Inventario dei fenomeni franosi in italia (iffi) - regione abruzzo.” https://idrogeo.isprambiente.it/app/page/open-data.

[28] ISPRA - Regione Lombardia, “Inventario dei fenomeni franosi in italia (iffi) - regione lombardia.” https://idrogeo.isprambiente.it/app/page/open-data.

[29] M. Carelli, M. Ceriani, E. Buccolini, and E. Valbuzzi, “Analisi del dissesto da frana in lombardia,” 2006.

[30] L. D’Alessandro, L. Del Sardo, M. Buccolini, E. Miccadei, T. Piacentini, and A. Urbani, “Analisi del dissesto da frana in abruzzo,” 2005.

[31] G. Boscaino, L. Del Sardo, F. Leonardis, and G. Pipponzi, “Piano stralcio di bacino per l’assetto idrogeologico,” 2021.