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Using deep convolutional neural networks for mapping of rill erosion of the Pre-Volga region (Republic of Tatarstan, Russia)

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ABSTRACT

Soil erosion all over the world is an intensive, poorly controlled process. In many ways, this is a consequence of the lack of up-to-date high-resolution erosion maps. All over the world, the problem of information insufficiency is solved in different ways, mainly point-by-point, in local territories. Extrapolation of locally obtained results to a larger area inevitably leads to uncertainties and errors. For the anthropogenically developed part of Russia, this problem is particularly relevant, because the assessment of the intensity of erosion processes, even with the use of erosion models, does not allow to achieve the required scale due to the lack of all the necessary global large-scale remote sensing data of the Earth and the complexity of considering regional features of erosion over such large areas. The paper proposes a new technique for automated large-scale mapping of erosion processes, namely rill erosion, according to Sentinel-2. Deep learning neural networks are used to recognize washouts. To recognize rills, a transfer learning approach was used, namely, a combination of the LinkNet architecture with the EfficientNetB3 encoder. The accuracy of automated recognition of rill erosion in the study area of 3,200 square kilometers is 80% compared to the results of manual recognition. The average density of the rill erosion was 0.3 km/sq.km, the maximum – 0.66 km/sq.km. The greatest density of washouts corresponds to the plowed deforested territories actively used in agriculture, the minimum – is on cultivated lands with contour farming.

Keywords: DNN, rill erosion, automatic recognition, Linknet, EfficientNet, Sentinel-2

1. INTRODUCTION

Soil erosion has been and remains the main factor in the degradation of the fertile layer of agricultural land. Intensive use of land in combination with natural factors creates conditions for intensifying the development of the so-called rill erosion, which includes gullies, erosion rills, and ephemeral ravines. Often, these erosional forms turn into permanent ravines, completely removing the territory from agricultural use. Therefore, it is not surprising that researchers all over the world pay special attention to the study of the problem of soil, and in particular, stream erosion.

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Both field and mathematical methods are used as the main methods for studying soil erosion. Field methods make it possible to estimate the volume of erosional changes very accurately, but in local areas, which somewhat complicates the spatial interpretation of the results obtained at the regional or landscape levels. These include the classical methods of reference areas, the benchmarks method, and microprofiling, taking the length and width of erosion with a measuring tape. Reference sites allow one to estimate the direct volume of soil washed off the territory by artificially changing the conditions of the "environment" [1]. Currently, geodetic methods are actively used to assess erosion, based on the reconstruction of the relief using laser scanning or photogrammetry data, both ground and air. The most accurate results can be achieved using terrestrial laser scanning data using reference points [2]. Researchers from all over the world record in this way not only ravine [3] or ripple [4], but also microrill and planar soil erosion [5], the variations of which are within the first millimeters. Unfortunately, it is problematic to use such technologies for direct monitoring in areas larger than 1 hectare. They try to solve this problem using airborne laser scanning; however, this technology has its limitations, primarily related to the positioning of the scanning equipment for subsequent resurvey equalization. This fact immediately excludes the possibility of using aerial scanning to assess the dynamics of microrill and planar erosion, however, it makes it possible to estimate the total length and width of rill and ravine erosion in a more or less automated mode. For this, various approaches are used, however, the most common one is based on the threshold value of the number of digital elevation model (DEM) cells from which flow into neighboring cells is possible. Depending on the resolution of the original DEM obtained from the scanned data, this approach makes it possible to recognize gullies with a depth of 5 cm or more. However, airborne laser scanning is not widely used due to the high cost of scanning equipment. Currently, inexpensive scanning sensors have appeared that can be installed not only on manned aircraft, but also on unmanned aerial vehicles (UAVs). However, the possibility of using such devices for solving the problem of soil erosion assessment has yet to be clarified - an analysis of existing experience has shown that the greatest applicability of such devices is in forestry [6]. Despite the current trend towards cheaper scanning systems, they are still inaccessible to most researchers. The combination of these factors has led to the fact that photosensors are the most widely used payload for UAVs [7]. UAV photogrammetry makes it possible to achieve a comparable density of a point cloud with scanning systems, a competitive accuracy of the resulting models, and to obtain an ultra-high-resolution orthophotomap as one of the final products. The use of UAVs provides geomorphological studies with up-to-date information on the state of the study area at a low cost, quickly, and fairly accurately. Unfortunately, despite the overall high performance, the use of UAVs does not allow continuous surveys of large regions [8,9], however, it does allow verification of model data.

To solve the problem of mapping rill erosion, considering the existing limitations, approaches are used based on the manual selection of erosion according to remote sensing data, namely satellite images [10,11]. Such a solution allows for achieving the best accuracy, but it is laborious and inefficient. To solve this problem, it is necessary to develop approaches based on the automation of the selection of rill washouts, which is the goal of this work. The initial data used as a cartographic basis defines a list of possible approaches that can be applied to achieve the goal. The simplest of them is the recognition of objects based on the threshold approach, where the threshold defines the limit of the reflectivity of the spectral data typical for the object of study. Such approaches are good for identifying different types of land use [12,13(p8)]. However, when recognizing rills using this approach on different soil types, the result will be unpredictable. To consider the spatial variability of environmental factors, machine learning methods can be used, for example, the well-established Random Forest method or Support Vector Machine [14,15]. However, such approaches only give the probability that there may be soil erosion in a particular pixel, without separating the erosions themselves into a "tree pattern". In addition, the methods are very sensitive to the amount of input data - the more information is used for analysis, the more stable the results will be. In small watersheds, such approaches can be successfully applied; for large areas, their applicability is questionable.

Recently, there has been a rapid increase in the number of works on the use of deep neural networks (DNN) for the semantic segmentation of remote sensing data. This was facilitated both by improving the quality of remote sensing data and by increasing the computing power available to researchers. Currently, DNNs make it possible to successfully solve problems of automated interpretation of anthropogenic objects [16–18], coastline [19,20], land use [21–23], and vegetation cover dynamics [24–26]. In all cases, the authors note a higher accuracy of recognition of objects of interest compared to other methods and emphasize the possibility of scaling the trained models. Deep neural networks were not used to solve the problem of recognition and mapping of rill erosion. However, the importance of the problem under study and the prospects for using artificial intelligence to solve this problem determine the need to develop an appropriate methodology.

2. STUDY AREA

The territory of the Buinsky and Tetyushsky municipal districts of the Republic of Tatarstan serves as the study area. The territory is located in the central part of the East European Plain [27] and is confined to the Pre-Volga region of the republic. The study area is 3,200 sq. km. The study area is completely included in the forest-steppe landscape zone (Fig. 1), has an average height of 120 m, and average slopes of 1.2–2 degrees. and is composed mainly of clayey and heavy loamy gray forest soils. There are also leached chernozems. Very favorable natural conditions ensure efficient agriculture, which has a strong impact on the natural-territorial complexes, primarily on the soil cover. Considering the intensity of plowing, livestock grazing, and natural conditions that contribute to the development of exogenous processes, this territory is highly susceptible to soil erosion.

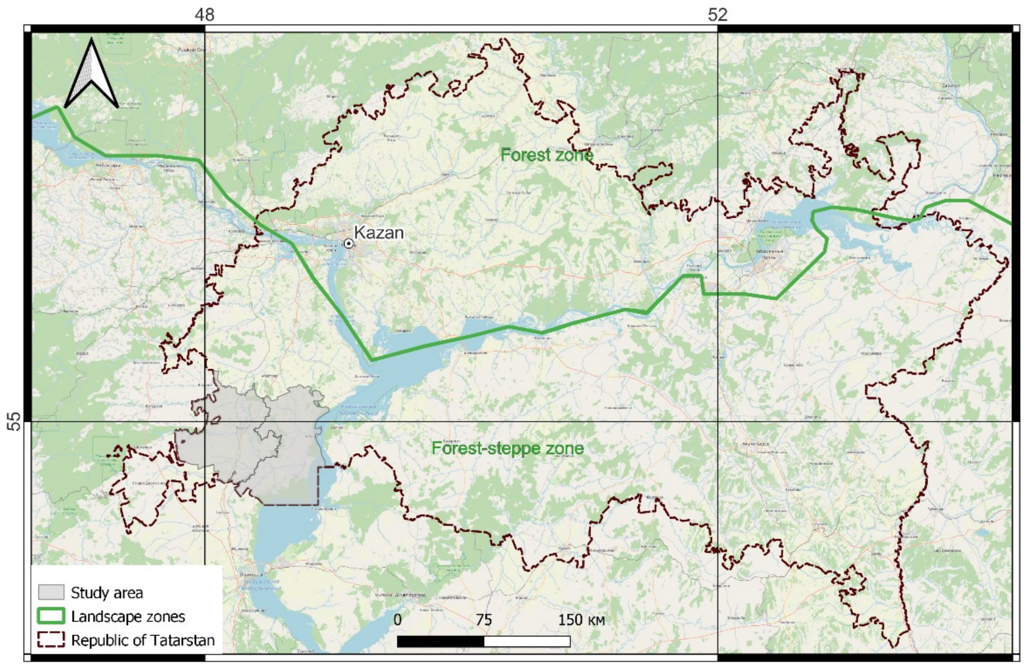

Figure 1. Study area.

3. MATERIALS AND METHODS

Data from the cloudless composite of the Sentinel-2 mission of the near-infrared range with the original resolution for the spring period (April-June) were used as initial data for the rill erosion recognition technique development. The composite was created using the Google Earth Engine (GEE) [28], “Sentinel-2 MSI: MultiSpectral Instrument, Level-2A” product (COPERNICUS/S2_SR). GEE allows the processing of large remote sensing data and facilitates some routine operations. To create a composite, the 2018–2019 images were filtered by date, the images were cleaned from clouds and shadows, the median pixel brightness values were calculated, and the images were cropped along the boundaries of the study area, as well as reprojected into the WGS 84/Pseudo-Mercator projection coordinate system (EPSG: 3857).

In the resulting spring composite, continuous manual recognition of rill erosion was performed to create a sample of reference data (Fig. 2).

The resulting sample was rasterized and reduced to the resolution of a satellite image fragment, then both rasters were cut into patches of 256*256 pixels. A total of 11,000 satellite image-binary mask pairs were obtained (Fig. 3). The resulting rasters were additionally randomly transformed to artificially increase the number of rasters by 3 times. The resulting dataset was divided into training and test sets of a 1/5 ratio.

LinkNet, a fully convolutional neural network for semantic image segmentation, was chosen as the neural network architecture [29]. Through the trial-and-error method, it became clear that the best results in rills interpretation can be achieved using transfer learning, a method of training deep neural networks that allows you to use the knowledge gained about one deep learning problem and apply it to another, but with a similar task. In our case, we used encoders applied for EfficientNetB3 image classification [30]. The algorithm for model training and applying was produced in the Python 3.7 programming environment using the Keras library. A stack of image-mask pairs, previously prepared at the previous stage, was sent to the input of the neural network. To prevent the model overfitting, EarlyStopping monitoring was used, and the IOU Score metric – the Jaccard coefficient [31] was used as a metric for checking the model trainability.

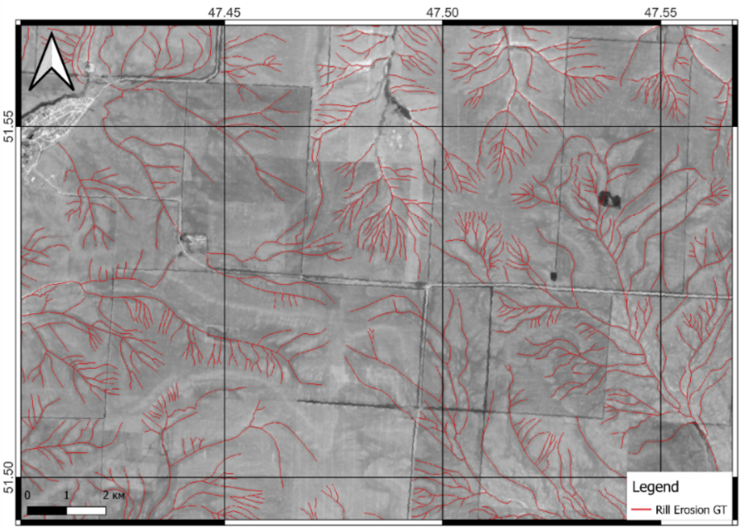

Figure 2. Example of training sample data.

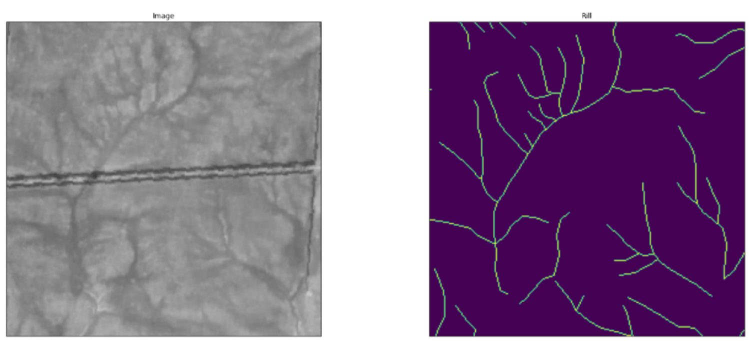

Figure 3. Example of satellite image patch (a) and binary mask (b) of training data.

4. RESULTS AND DISCUSSION

The trained neural network was tested on an independent dataset. The recognition accuracy was 0.67, the F1-measure – was 0.8, and the loss function – was 0.21. As a result of a qualitative analysis of the semantic segmentation results (Fig. 4), a fairly high level of the rill net recognition, including visually, was obtained. Not a single case of ravines or dirt roads identifying instead of rills must be recorded.

It was decided to apply the trained and tested model throughout the study area (Fig. 5). The length of the resulting rill geometry was recalculated into a basins grid [32] (Fig. 6).

The average density of rill erosion – was 0.3 km/km^2, and the maximum density was 0.66 km/km^2. The highest rills density corresponds to plowed deforested areas actively used in agriculture, and the minimum density – is to cultivated lands with contour farming. The results obtained, in general, are in good agreement with the data on the gully density assessment, as the next evolutionary stage in the development of the erosion belt [33].

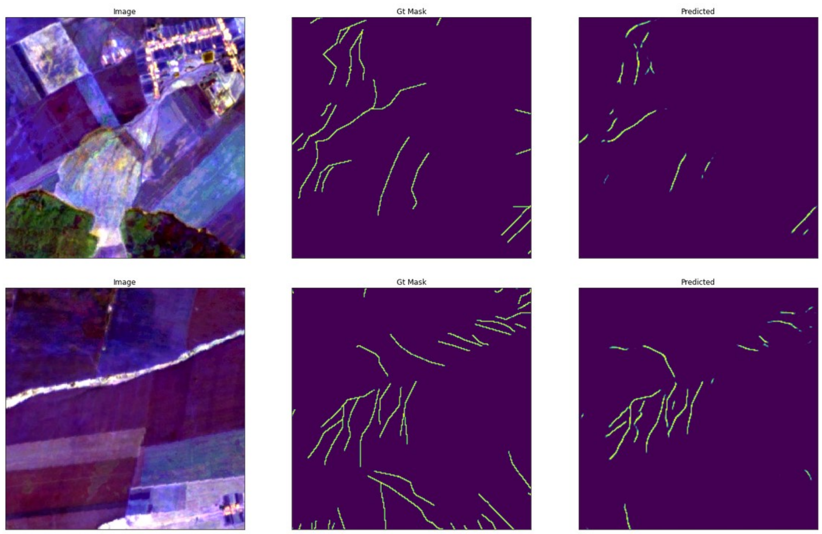

Figure 4. Semantic segmentation of rill erosion. From left to right, a fragment of the satellite image, the results of manual detection of washouts, and the results of automated detection of washouts.

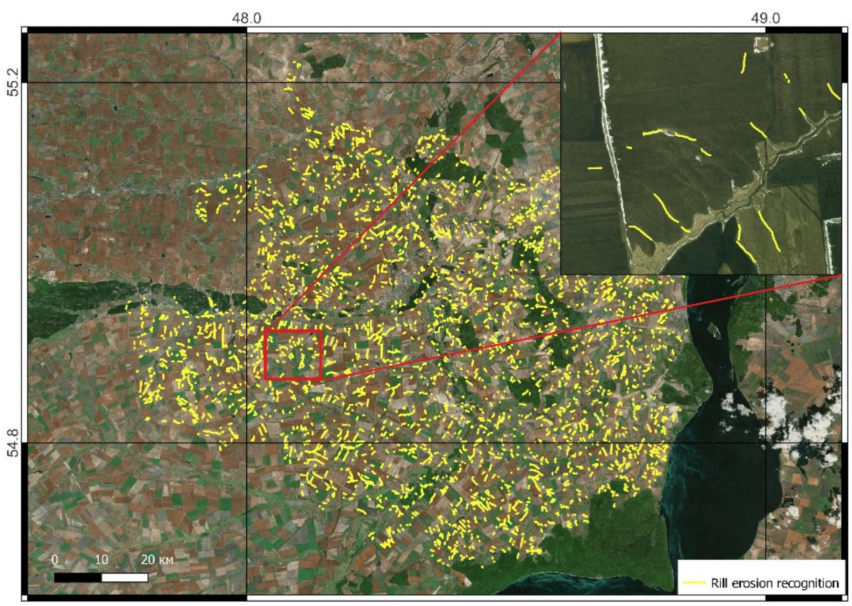

Figure 5. Results of automated mapping of rill erosion.

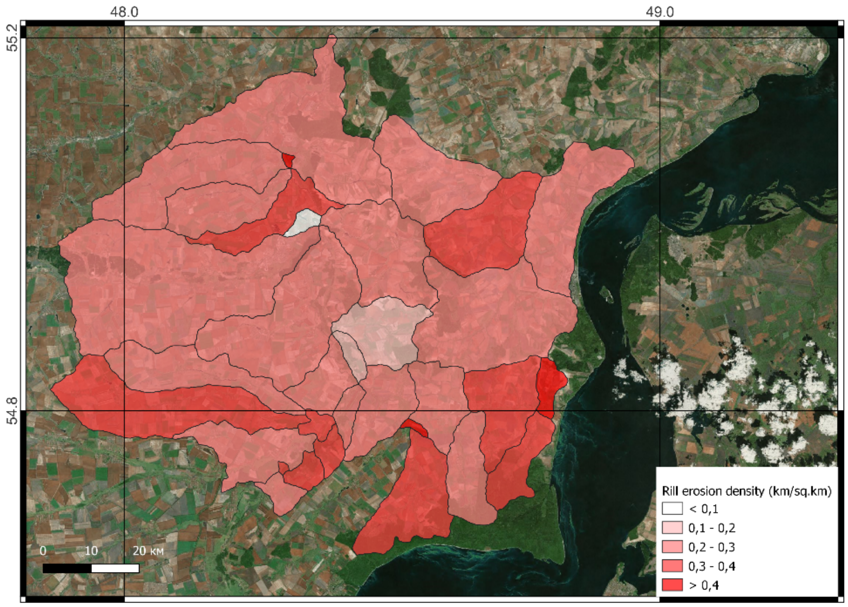

Figure 6. Map of rill erosion in the Pre-Volga region of the Republic of Tatarstan.

5. CONCLUSION

Deciphering the rill element of soil erosion according to remote sensing data is a complex and time-consuming task. The use of modern convolutional neural networks makes it possible to speed up rill net mapping many times over, and the presence of a constantly updated high-resolution satellite images catalog makes it possible for an up-to-date assessment of the erosion network development. In general, the achieved level of accuracy of the erosion network pattern recognition is already sufficient for large-scale mapping, however, the accuracy of semantic segmentation can be improved. For example, it seems promising to use as initial data not direct satellite images of Sentinel 2, but derivatives in the form of vegetation indices rasters, for example, NDVI. It is also possible to use more complex encoders with a much larger number of model parameters, such as EfficientNetB7.

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REFERENCES

[1] Yang, Y., Shi, Y., Liang, X., Huang, T., Fu, S. and Liu, B., “Evaluation of structure from motion (SfM) photogrammetry on the measurement of rill and interrill erosion in a typical loess,” Geomorphology 385, 107734 (2021).

[2] Yermolaev, O. P., Gafurov, A. M. and Usmanov, B. M., “Evaluation of Erosion Intensity and Dynamics Using Terrestrial Laser Scanning,” Eurasian Soil Sci. 51(7), 814–826 (2018).

[3] Kociuba, W., Janicki, G., Rodzik, J. and Stępniewski, K., “Comparison of volumetric and remote sensing methods (TLS) for assessing the development of a permanent forested loess gully,” Nat. Hazards 79(S1), 139–158 (2015).

[4] Vinci, A., Brigante, R., Todisco, F., Mannocchi, F. and Radicioni, F., “Measuring rill erosion by laser scanning,” CATENA 124, 97–108 (2015).

[5] Usmanov, B., Yermolaev, O. and Gafurov, A., “Estimates of slope erosion intensity utilizing terrestrial laser scanning,” Proc. Int. Assoc. Hydrol. Sci. 367, 59–65 (2015).
[6] Hu, T., Sun, X., Su, Y., Guan, H., Sun, Q., Kelly, M. and Guo, Q., “Development and Performance Evaluation of a Very Low-Cost UAV-Lidar System for Forestry Applications,” 1, Remote Sens. 13(1), 77 (2021).
[7] Nex, F. and Remondino, F., “UAV for 3D mapping applications: a review,” Appl. Geomat. 6(1), 1–15 (2014).
[8] Gafurov, A. M., “Possible Use of Unmanned Aerial Vehicle for Soil Erosion Assessment,” Uchenye Zap. Kazan. Univ.-Seriya Estestv. Nauki 159(4), 654–667 (2017).
[9] Gafurov, A., “The Methodological Aspects of Constructing a High-Resolution DEM of Large Territories Using Low-Cost UAVs on the Example of the Sarycum Aeolian Complex, Dagestan, Russia,” Drones 5(1), 7 (2021).
[10] Yermolaev, O. P., Medvedeva, R. A. and Platoncheva, E. V., “Methodological Approaches to Monitoring Erosion of Agricultural Lands in the European Part of Russia by Using Satellite Imagery,” Uchenye Zap. Kazan. Univ.-Seriya Estestv. Nauki 159(4), 668–680 (2017).
[11] Yermolayev, O., Platoncheva, E. and Essuman-Quainoo, B., “Spatial-Temporal Dynamics of the Ephemeral Gully Belt on the Plowed Slopes of River Basins in Natural and Anthropogenic Landscapes of the East of the Russian Plain,” 5, Geosciences 10(5), 167 (2020).
[12] Walter, V., “Object-based classification of remote sensing data for change detection,” ISPRS J. Photogramm. Remote Sens. 58(3), 225–238 (2004).
[13] Zhang, F., Li, J., Zhang, B., Shen, Q., Ye, H., Wang, S. and Lu, Z., “A simple automated dynamic threshold extraction method for the classification of large water bodies from landsat-8 OLI water index images,” Int. J. Remote Sens. 39(11), 3429–3451 (2018).
[14] Dinh, T. V., Nguyen, H., Tran, X.-L. and Hoang, N.-D., “Predicting Rainfall-Induced Soil Erosion Based on a Hybridization of Adaptive Differential Evolution and Support Vector Machine Classification,” Math. Probl. Eng. 2021, e6647829 (2021).
[15] Ghosh, A. and Maiti, R., “Soil erosion susceptibility assessment using logistic regression, decision tree and random forest: study on the Mayurakshi river basin of Eastern India,” Environ. Earth Sci. 80(8), 328 (2021).
[16] Liu, Y., Zhou, J., Qi, W., Li, X., Gross, L., Shao, Q., Zhao, Z., Ni, L., Fan, X. and Li, Z., “ARC-Net: An Efficient Network for Building Extraction from High-Resolution Aerial Images,” IEEE Access 8, 154997–155010 (2020).
[17] Cai, J. and Chen, Y., “MHA-Net: Multipath Hybrid Attention Network for Building Footprint Extraction from High-Resolution Remote Sensing Imagery,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 14, 5807–5817 (2021).
[18] Luo, L., Li, P. and Yan, X., “Deep learning-based building extraction from remote sensing images: A comprehensive review,” Energies 14(23) (2021).
[19] Aryal, B., Escarzaga, S. M., Vargas Zesati, S. A., Velez-Reyes, M., Fuentes, O. and Tweedie, C., “Semi-automated semantic segmentation of arctic shorelines using very high-resolution airborne imagery, spectral indices and weakly supervised machine learning approaches,” Remote Sens. 13(22) (2021).
[20] Blais, M.-A. and Akhloufi, M. A., “Deep learning for low altitude coastline segmentation,” presented at Proceedings of SPIE - The International Society for Optical Engineering, 2021.
[21] Dong, Y., Li, F., Hong, W., Zhou, X. and Ren, H., “Land cover semantic segmentation of Port Area with High Resolution SAR Images Based on SegNet,” presented at 2021 SAR in Big Data Era, BIGSARDATA 2021 - Proceedings, 2021.
[22] Garg, R., Kumar, A., Bansal, N., Prateek, M. and Kumar, S., “Semantic segmentation of PolSAR image data using advanced deep learning model,” Sci. Rep. 11(1), 15365 (2021).
[23] Wei, H., Xu, X., Ou, N., Zhang, X. and Dai, Y., “Deanet: Dual encoder with attention network for semantic segmentation of remote sensing imagery,” Remote Sens. 13(19) (2021).
[24] Illarionova, S., Trekin, A., Ignatiev, V. and Oseledets, I., “Tree species mapping on sentinel-2 satellite imagery with weakly supervised classification and object-wise sampling,” Forests 12(10) (2021).
[25] Du, B., Zhao, Z., Hu, X., Wu, G., Han, L., Sun, L. and Gao, Q., “Landslide susceptibility prediction based on image semantic segmentation,” Comput. Geosci. 155 (2021).
[26] Song, G., Wu, S., Lee, C. K. F., Serbin, S. P., Wolfe, B. T., Ng, M. K., Ely, K. S., Bogonovich, M., Wang, J., Lin, Z., Saleska, S., Nelson, B. W., Rogers, A. and Wu, J., “Monitoring leaf phenology in moist tropical forests by applying a superpixel-based deep learning method to time-series images of tree canopies,” ISPRS J. Photogramm. Remote Sens. 183, 19–33 (2022).

[27] Yermolaev, O., Mukharamova, S. and Vedeneeva, E., “River runoff modeling in the European territory of Russia,” CATENA 203, 105327 (2021).
[28] Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R., “Google Earth Engine: Planetary-scale geospatial analysis for everyone,” Remote Sens. Environ. 202, 18–27 (2017).
[29] Chaurasia, A. and Culurciello, E., “LinkNet: Exploiting encoder representations for efficient semantic segmentation,” 2017 IEEE Vis. Commun. Image Process. VCIP, 1–4 (2017).
[30] Tan, M. and Le, Q., “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” Proc. 36th Int. Conf. Mach. Learn., 6105–6114, PMLR (2019).
[31] Jaccard, P., “The distribution of the flora in the alpine zone,” New Phytol. 11(2), 37–50 (1912).
[32] Yermolaev, O. P., Mukharamova, S. S., Maltsev, K. A., Ivanov, M. A., Ermolaeva, P. O., Gayazov, A. I., Mozzherin, V. V., Kharchenko, S. V., Marinina, O. A. and Lisetskii, F. N., “Geographic Information System and Geoportal «River basins of the European Russia»,” IOP Conf. Ser. Earth Environ. Sci. 107, 012108 (2018).
[33] Golosov, V., Yermolaev, O., Rysin, I., Vanmaercke, M., Medvedeva, R. and Zaytseva, M., “Mapping and spatial-temporal assessment of gully density in the Middle Volga region, Russia,” Earth Surf. Process. Landf. 43(13), 2818–2834 (2018).