Mapping Drainage Ditches in Forested Landscapes Using Deep Learning and Aerial Laser Scanning

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Abstract: Extensive use of drainage ditches in European boreal forests and in some parts of North America has resulted in a major change in wetland and soil hydrology and impacted the overall ecosystem functions of these regions. An increasing understanding of the environmental risks associated with forest ditches makes mapping these ditches a priority for sustainable forest and land use management. Here, we present the first rigorous deep learning–based methodology to map forest ditches at regional scale. A deep neural network was trained on airborne laser scanning data (ALS) and 1,607 km of manually digitized ditch channels from 10 regions spread across Sweden. The model correctly mapped 86% of all ditch channels in the test data, with a Matthews correlation coefficient of 0.78. Further, the model proved to be accurate when evaluated on ALS data from other heavily ditched countries in the Baltic Sea Region. This study leads the way in using deep learning and airborne laser scanning for mapping fine-resolution drainage ditches over large areas. This technique requires only one topographical index, which makes it possible to implement on national scales with limited computational resources. It thus provides a significant contribution to the assessment of regional hydrology and ecosystem dynamics in forested landscapes. **DOI: 10.1061/JIDEDH.IRENG-9796.**

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Introduction

Digging drainage ditches is common forestry practice across northern European boreal forests and in some parts of North America (Lõhmus et al. 2015). Ditching helps with lowering the groundwater level in the wet parts of the forest to improve soil aeration and support tree growth (Laurén et al. 2021; Sikström and Hökkä 2016). Some of the most drained countries include Finland, the Baltic States, and parts of Sweden, where the drained forest stands comprise 20%–25% of the total forest area (Nieminen et al. 2018). However, the extensive use of ditches over a long period of time has resulted in a major change in wetland and soil hydrology and impacted the overall ecosystem functions of these regions (Kuglerová et al. 2020).

Recently, the intensive ditching practice has been identified as posing multiple environmental risks, particularly for degradation of wetland and soil, greenhouse gas emissions (Audet et al. 2017; Peacock et al. 2021), increased nutrient and sediment loadings to water bodies, and biodiversity loss (Holden et al. 2004; Lepistö et al. 2021; Lidman et al. 2017; Lõhmus et al. 2015; Nieminen et al. 2018). Research and actions were set up to minimize environmental loss and restore degraded land in the ditched forest landscape. However, such initiatives are significantly constrained by the lack of accurate and site-specific information of ditch networks. For example, a comparison between a national field inventory (Ståhl et al. 2011) and the best available high-resolution map of Sweden suggests that only 9% of the ditches that were inventoried by the national field inventory are mapped on current maps. In addition, 68% of the field-mapped channels were ditches, highlighting the scale of this lack of knowledge. A study in northern Sweden documented that accounting for all ditches nearly doubled the size of the stream network within a 68-km^2 catchment (Hasselquist et al. 2018). These findings are a clear indication that there is a discrepancy between the potential significance of artificial water bodies, such as drainage ditches, and their low representation in scientific research and policy (Koschorreck et al. 2020). The increasing understanding of the environmental risks associated with forest ditches, together with the poor representation of ditch networks in existing maps of many forest landscapes, makes detailed

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mapping of these ditches a priority for sustainable land and hydrological management.

The availability of high-quality remote sensing data has enabled successful mapping of different landscape features; accordingly, satellite-based hydrological analysis has become an effective tool for the assessment of water resources across the globe (McCabe et al. 2017). In open landscapes, such as agricultural lands or open peatlands, ditches can be detected from satellite images or aerial photos (Ayana et al. 2017). But mapping ditches in a forest landscape remains a significant challenge, given that such features are obscured by the tree canopy cover (Benstead and Leigh 2012; Hasselquist et al. 2018). A common solution for mapping small-scale watercourses in such landscapes (Benstead and Leigh 2012) is to model the accumulated flow from a digital terrain model and set a stream initiation threshold for extracting the stream networks. The stream initiation threshold refers to how large a drainage area is required to initiate a stream. However, the formation of stream heads varies depending on climate, topography, and soil conditions (Elmore et al. 2013; Jensen et al. 2017; Julian et al. 2012; Russell et al. 2015). Moreover, in landscapes where channels have been altered by humans, such as in the case of ditches, channel formation is no longer controlled by natural erosion. Hence, the flow accumulation–based hydrological modeling approach does not adequately capture a heavily modified ditch network in forested landscapes.

More recently, deep learning approaches have emerged as a mainstay of data processing and analysis in the field of water resources (Sit et al. 2020). Airborne laser scanning (ALS) data of high point density are being integrated with powerful machine learning and statistical tools to map ditches. Most ditch detection studies used ALS-derived digital elevation models (DEMs) but focused only on smaller study areas of up to 150 ha (Cazorzi et al. 2013; Rapinel et al. 2015; Roelens et al. 2018a, b). In addition, those ditch detection studies were predominantly performed in open areas, such as French marshes (Rapinel et al. 2015) and vineyards (Bailly et al. 2008), Belgian grasslands and peri-urban areas (Roelens et al. 2018b), Italian and US agrarian landscapes (Cazorzi et al. 2013; Passalacqua et al. 2012), Chinese rice fields (Qian et al. 2018), or near roads in Finland (Kiss et al. 2015). In such open landscapes, ditch detection is comparatively less complex, as tree cover is rare, and ditches are usually well maintained in these populated, easily accessed, managed landscapes.

These ditch detection methods using ALS data in open landscapes generally use data filtering to highlight ditches: for example, wavelet transformation (Bailly et al. 2008), relative elevation attribute (Cazorzi et al. 2013; Roelens et al. 2018b), geometric and Laplacian curvature (Passalacqua et al. 2012), linear filter (Rapinel et al. 2015), or topographic position index and standardized elevation index (Kiss et al. 2015). Data filtering follows a binary classification of raster layers into ditches and nonditches, while the classification can be performed on ALS point clouds, pixels, or linear objects depending on the chosen method. Different classification approaches have been used for binary classification, such as manual setting of thresholds using expert knowledge (Kiss et al. 2015; Passalacqua et al. 2012), logistic regression (Roelens et al. 2018b), and application of machine learning models (Bailly et al. 2011; Roelens et al. 2018a).

Deep learning presents a new avenue for data-driven hydrological analysis and modeling, especially with high-resolution imagery. Semantic image segmentation using deep learning is on the rise for many applications, from autonomous driving to virtual or augmented reality systems (Garcia-Garcia et al. 2017). However, the use of deep learning for image analysis in hydrological research remains limited. Deep learning techniques use multilayer models that can effectively capture the underlying complexity in heterogeneous hydrological systems (Sit et al. 2020). Deep learning can be effective for extracting small-scale hydrological features and can reduce prediction uncertainty by being insusceptible to raw and noisy data (Shen et al. 2018). Here, we developed a novel methodology by combining two state-of-the-art technologies—ALS and deep learning—for detecting drainage ditches in forested landscapes. We then validated the methodology using data from multiple countries in Northern Europe. To the best of our knowledge, this approach to detecting ditches has not been reported in the literature previously.

Method

We trained a deep neural network on high-density ALS data and manually digitized ditches from 10 regions across Sweden. We set aside 20% of the data for testing the final model. In addition to this testing data, the model was applied to four additional test areas spread across Sweden, Finland, Latvia, and Poland [Fig. 1(a)].

Training Dataset

The 10 digitized forest-dominated regions were selected to achieve a broad representation of different landscape properties concerning topography, soil conditions, runoff, land use, and tree species. A compact laser-based system (Leica ALS80-HP-8236) was used to collect the ALS data from an aircraft flying at 2,888–3,000 m. The ALS point clouds had a point density of one to two points per m^2 and were divided into 55 tiles with a size of 2.5×2.5 km each. Combined, the tiles cover an area of 344 km^2. DEMs with 0.5-m resolution were created from the ALS point clouds using a tin-gridding approach implemented in Whitebox tools 1.4.0 (Lindsay 2018). A high-pass median filter (HPMF) was applied to the DEMs to emphasize short-range variability in the topography. The HPMF algorithm, implemented in Whitebox tools (Lindsay 2018), operates by subtracting the value at the grid cell at the center of the window from the median value in the surrounding neighborhood with a kernel of 11 cells. Negative values indicate depressions, and positive values indicate ridges.

Labels

Ditches were manually digitized as vector lines by trained experts who were calibrated among themselves with regular meetings and discussions of "edge cases". Multidirectional hill-shaded DEMs and a HPMF were used to visually separate local ridges from local depressions (e.g., ditch channels). Current and historical orthophotos and maps were used to corroborate edge cases to digitize the ditch network. Of the 55 tiles, 20% ($n = 11$) were randomly selected for model testing and were not used to train the model [Fig. 1(b)]. The digitized vector lines have no width, so we used average ditch width from a field inventory during which 2,188 ditch channels were visited across Sweden (Ståhl et al. 2011). The average ditch width was 2 m, with a standard deviation of 1.3 m. Instead of flagging all pixels within ~3 m of a vector line as ditch, we used the HPMF to create more natural ditch labels. Pixels within 3 m of a vector line and with a HPMF value less than −0.075 were flagged as ditch pixels. The threshold value of −0.075 was selected based on visual observations of ditch channels during digitalization of the ditches. Spurious pixels that were not connected to a ditch were removed using a majority filter with a three-cell kernel. In total 1,607 km of ditch channels were mapped in this manner (Ågren et al. 2022).

Deep Learning Model

The HPMF and labeled data from each of the 55 tiles were split into pairs of image chips with 512×512 pixels in each chip [Fig. 1(c)]. Image chips in which ditches made up less than 0.1% of all pixels in the chip were removed to combat the highly imbalanced class distribution: clearly, most pixels in the data are nonditch. This resulted in 2,367 pairs of image chips. We used TensorFlow 2.6 to build an encoder-decoder style deep neural network, shown in Fig. 2, to transform the filtered HPMF images into images highlighting the detected ditches. On the encoding path, the network learns a series of filters, organized in layers, that express larger and larger neighborhoods of pixels in fewer and fewer vectors of features. This downsampling forces the network to ignore noise and extract features relevant for ditch detection. In contrast to normal

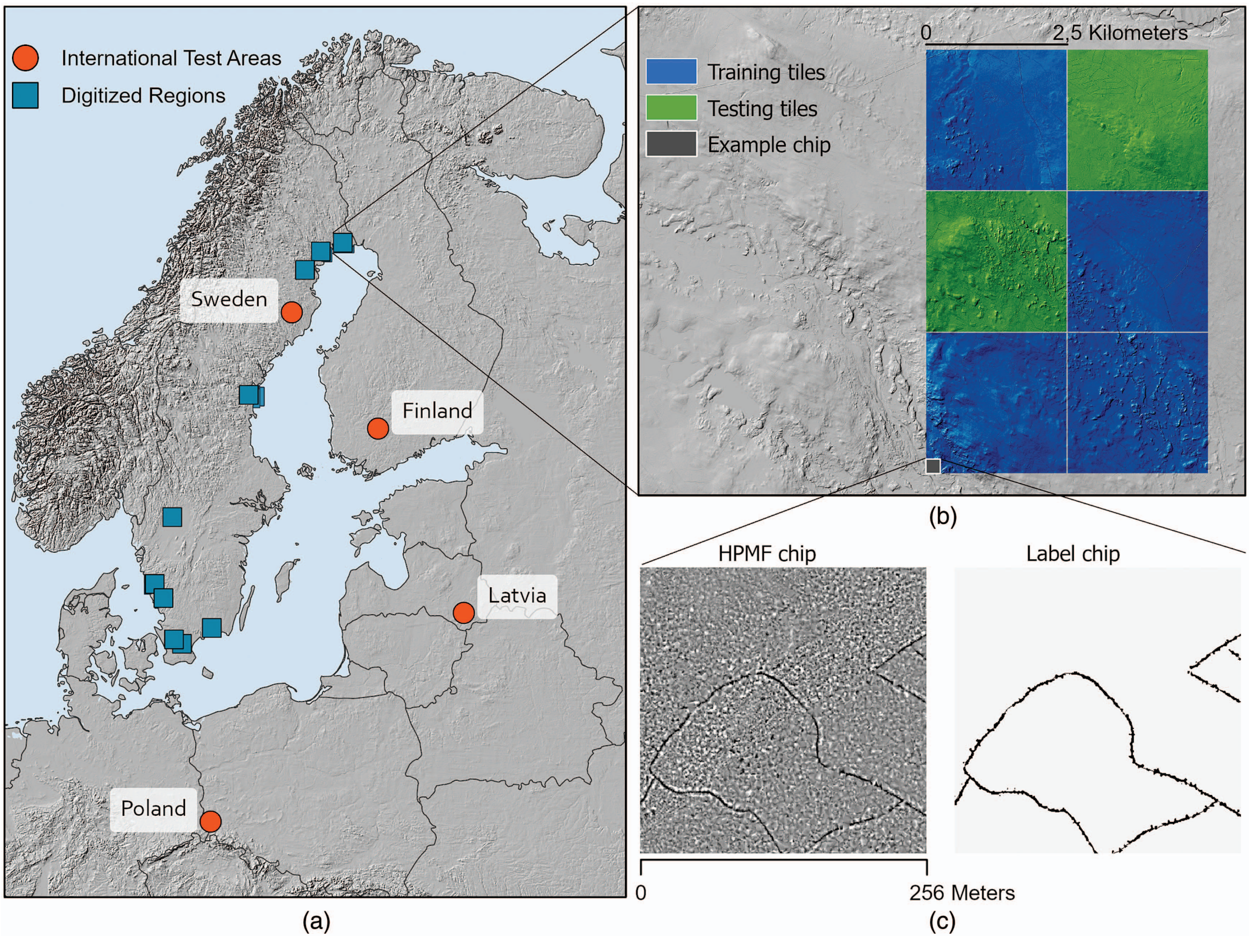

Fig. 1. (Color) Training and testing data. (a) Blue squares indicate locations of the digitized regions with training/testing data, and red points indicate locations of the additional international test areas (not drawn to scale). (b) Close-up of one digitized region. Each region consisted of tiles with the size 2.5×2.5 km. These tiles were split into smaller 512×512-pixel image chips that were used to train and test the model. Image chips from the blue tiles were used for training, and image chips from the green tiles were used for testing. (c) Example of an HPMF image chip and corresponding label chip. (Base maps created using the SRTM30+ Global 1-km Digital Elevation Model.)

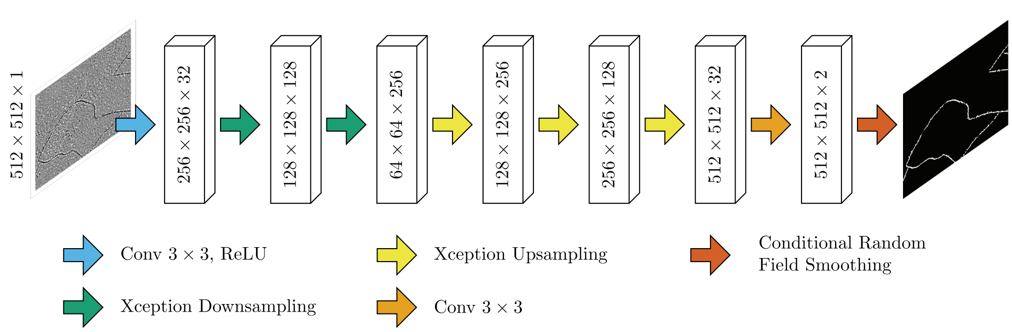

Fig. 2. (Color) Overall network architecture. Its structure consists of a downsampling path, which learns the compact representation of input data, and an upsampling path, which decompresses it to reconstruct the input data. The intermediate blocks show the number and size of the created feature maps. The input is a high-pass median filter from an ALS DEM, and the output is an image in which each pixel represents the probability of the corresponding pixel being classified as a ditch.

convolutional neural networks, which apply a filter to all feature vectors in a certain spatial neighborhood at once, we use Xception blocks (Chollet 2017). These blocks decouple the filtering of the spatial neighborhood within each feature dimension from the filtering across feature dimensions. This simplifies the learning problem for ditch detection, since there is no strong coupling between the two dimensions.

After encoding the HPMF image into a spatially more compact representation, it was again decoded by a series of learned filters performing transposed convolutions into the final classification map. This map contains, for every pixel in the input image, the probability that the pixel belongs to a ditch. Although the neural network considers the neighborhood of the pixel to label that pixel, the procedure still leads to label discontinuities, either in the form of ditches disrupted by mislabeled nonditch pixels or in the form of areas of nonditch pixels in which single pixels are labeled as ditch pixels. To smooth out this type of noise, we use a conditional random field layer proposed by Zheng et al. (2015), which learns to penalize undue label discontinuities. This neural network model is trained using weighted cross-entropy loss to deal with the large class imbalance between ditch and nonditch pixels.

Evaluation

We evaluated the trained model on the set-aside test tiles ($n = 11$) as well as on four additional test areas in Sweden (a 68-km^2 area scanned with 20 points per m^2), Finland (a 70-km^2 area scanned with five points per m^2), Latvia (a 25-km^2 area scanned with four points per m^2), and Poland (a 44-km^2 area scanned with four points per m^2) [Fig. 1(a)]. Note that the test sites outside of Sweden were not digitized by the same team of experts that digitized the Swedish training and testing data.

The datasets are highly imbalanced. Therefore, we used several metrics, such as Cohen's κ and the Matthews correlation coefficient (MCC), to assess the accuracy of the model. Additional metrics were extracted to compare the performance of our model with 13 other ditch-mapping studies published between 2008 and 2020. Most of the previous studies reported inadequate accuracy measures for highly imbalanced binary prediction. Therefore, we included a large number of accuracy measures to enhance the confidence in our prediction.

Table 1. Confusion matrix showing the number of true positive (TP), false positive (FP), false negative (FN), and true negative (TN) predictions

Confusion matrix	Labeled positive	Labeled negative
Predicted positive	TP: 1,518,628	FP: 616,484
Predicted negative	F: 248,361	TN: 127,902,095

Results

Performance on Test Tiles

The performance of the model was evaluated by comparing predicted pixels with labeled pixels in the test data using a confusion matrix (Table 1). The model correctly predicted 99% of all pixels in the test data and achieved an MCC and κ of 0.78. Visual inspections of false-positive classifications indicated that the model interpreted most channels in the landscape as ditch channels and failed to distinguish natural stream channels from drainage ditches.

Although it was difficult to compare these results with models developed and tested in different landscapes and on different ALS data, the metrics were on par with or better than previous studies. Different studies presented different metrics, and the most commonly used metrics are summarized in Table 2.

Performance on Additional Test Sites

In addition to evaluating the model on the test tiles, we applied the model on ALS data from four additional study areas spread across the Baltic Sea region. The model achieved the highest MCC in Poland and the lowest MCC in Latvia (Fig. 3).

Discussion

Most previous ditch detection studies focused only on study areas smaller than 100 km^2 within predominantly open areas. Here, we introduce a large dataset with 1,607 km of mapped ditch channels spread across 344 km^2 in a landscape mainly dominated by forest. We demonstrate that our approach of combining deep learning with high-density ALS data to map drainage ditches has accuracy equal to or higher than that of previous studies. However, the studies by Graves et al. (2020), Kiss et al. (2015), Larson and Trivedi (2011), Rapinel et al. (2015), Stanislawski et al. (2018) reported only recall, which made them difficult to evaluate. Additional metrics on false positives would be helpful for a comparison with our results. It needs to be emphasized that we used only one topographical index

Table 2. A comparison of the performance of the deep-learning model developed in this study and other published approaches of mapping drainage ditches

Study	Recall (%)	Overall accuracy (%)	Precision	κ	MCC	Error of omission (%)	Error of commission (%)
Present study	86	99	0.71	0.78	0.78	14	29
Flykt et al. (2022)	70	91–99	0.77	0.73	—	—	—
Roelens et al. (2018a)	—	—	—	0.73–0.77	—	29–33	11–18
Broersen et al. (2017)	75–98	—	—	—	—	2–24	8–17
Roelens et al. (2018b)	—	—	—	—	—	8	5
Bailly et al. (2008)	—	70	—	—	—	50	15
Qian et al. (2018)	—	—	—	0.77	—	10	30
Ayana et al. (2017)	—	—	—	—	—	31–38	3
Balado et al. (2019)	—	50–65	—	—	—	—	—
Kiss et al. (2015)	60–80	—	—	—	—	—	—
Larson and Trivedi (2011)	31–89	—	—	—	—	—	—
Stanislawski et al. (2018)	90	—	—	—	—	—	—
Graves et al. (2020)	67–78	—	—	—	—	—	—
Rapinel et al. (2015)	50–60	—	—	—	—	—	—

Note: Balado et al. (2019) reported values of low overall accuracy, which appears unlikely and might thus refer to recall instead.

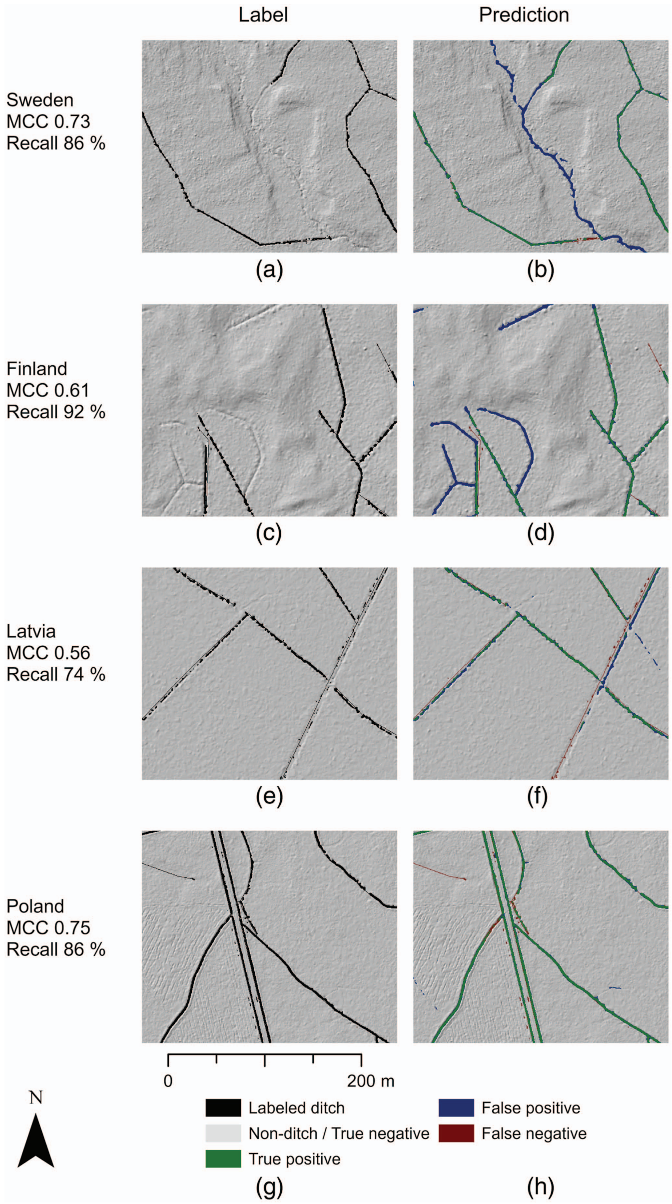

Fig. 3. (Color) Predicted ditch pixels from the international test areas: (a) labeled ditches in Sweden; (b) predicted ditches in Sweden; (c) labeled ditches in Finland; (d) predicted ditches in Finland; (e) labeled ditches in Latvia; (f) predicted ditches in Latvia; (g) labeled ditches in Poland; and (h) predicted ditches in Poland. The statistical evaluation was based on the whole study regions, while the maps in this figure highlight details in small areas.

to achieve this high accuracy, while other studies, such as Roelens et al. (2018a), relied on multiple indices for mapping drainage ditches in a smaller landscape (i.e., 68 km^2). This substantially enhances the utility of our methodology, especially for implementing it at large spatial scales with limited computational resources. The model could map an area of 1 km^2 in 8.6 s using a GeForce GTX 1080 Ti Graphics Card. Still, it will be worth exploring whether adding more indices besides HPMF can improve the prediction accuracy. For example, a recent study in Finland by Bhattacharjee et al. (2021) demonstrated that aerial photos may contain important information for mapping drainage ditches on peatlands. However, in areas hidden beneath canopy, it might be better to include topographical indices such as impoundment size index implemented in Whitebox tools 1.4.0 (Lindsay 2018), which can be included as multiband images. Thus, it seems worthwhile to explore these indices as additional covariates in the deep neural network model for future analysis.

Considering the inherent challenges of the study region's glaciated and forested landscape, the performance of our ditch mapping approach was highly successful. For instance, the landscape presented substantial challenges due to landscape features that appear similar to ditch channels in the ALS data. These include natural streams, historical channels from the latest deglaciation, ravines on sediment soils, and variability in larger-scale topography from steep mountains to flat mires or smaller agricultural areas interspersed in the forest landscape. Although our model produced a fair amount of false positives in the sedimentary deposits in the Swedish test catchment, the overall performance of the model was notably better than the previous ditch mapping studies that were conducted in relatively less challenging, more homogeneous landscapes. Some of the false positives in our prediction might even be actual ditches that are missing or misplaced in the ground-truth digitized data [blue lines in Figs. 3(d and f)]. This is likely because of the differences in digitization approaches in the international datasets. Hence, the accuracy measures calculated from the international validation datasets should be interpreted cautiously. The high MCC and recall values of ditch prediction in the international test sites indicate that the developed methodology performs well in all countries around the Baltic Sea, although the model was developed based on training data from Sweden. The trained model can be adjusted for local conditions with transfer learning using local data.

Visual inspection of the test sites revealed that some of the false positives were natural stream channels, as demonstrated in Fig. 3(b). This suggests that it could be possible to train a deep neural network to detect natural stream channels in addition to drainage ditches. This needs to be explored in the future with additional ground-truth data on natural stream channels. A model that can map natural stream channels would complement traditional topographical modeling of accumulated flows from digital terrain models, especially if the model can map headwater stream channels, as these are often missing on current maps (Benstead and Leigh 2012), and deal with road embankments, which make small streams difficult to map using traditional topographical modeling of low accumulation (Lidberg et al. 2017).

The management of water systems is key to sustainable development, but headwater streams (Bishop et al. 2008) and artificial drainage ditches are often not included in monitoring programs (Koschorreck et al. 2020). This has large implications for future research and practical land-use management, as the ditch networks have legacy effects on greenhouse gas balance, water resources, and biodiversity. Ditches possess particular characteristics that often make them emit large amounts of greenhouse gases (Peacock et al. 2021). Specifically, the accumulation of sediment and the development of anoxia result in favorable conditions for the production of the potent greenhouse gas methane (Roulet and Moore 1995). Emissions of nitrous oxide (N_2O) and carbon dioxide (CO_2) can be disproportionately large compared with the small areal extent of ditch surfaces (Audet et al. 2017; Peacock et al. 2019). In countries such as Sweden and Finland, which have significant areas of land drained for agriculture or forestry, these greenhouse gas emissions can make nonnegligible contributions to national greenhouse gas budgets (Koschorreck et al. 2020). Further, it is unclear whether peatland restoration or ditch cleaning to maintain forest growth is the best strategy to avoid negative environmental outcomes in the future. Mapping the drainage ditches in the forest landscape is necessary to address these important sustainability questions.

Conclusions

Mapping drainage ditches is an important first step in finding effective landscape and hydrology management strategies. We showed that semantic image segmentation with deep learning from high-resolution ALS data can be used to detect previously unmapped drainage ditches in forested landscapes in the Baltic Sea region with an overall accuracy of 99% and an MCC of 0.78. This novel technique requires only one topographical index, which makes it possible to implement on large scales with limited computational resources. Our method performs better on most of the metrics than previous ditch detection studies and at least equally well on all others, despite a more varied and challenging landscape in our test data dominated by forests. Visual inspection indicated that this method also classifies natural stream channels as ditches, which suggests that a deep neural network can be trained to detect natural stream channels in addition to drainage ditches.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available in a repository online in accordance with funder data retention policies. The code and a reproducible example are available from github (Lidberg et al. 2021). The data are available from Mendely data (Ågren et al. 2022), doi: 10.17632/zxkg43jsx8.1.

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