# LIDAR DECISION SUPPORT TOOL FOR FOREST DRAINAGE MAINTENANCE

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**Abstract.** Drainage maintenance in boreal and hemiboreal forests is increasingly recognised as a decision problem that requires spatially explicit information on ditch condition, network connectivity and expected hydrological outcomes of intervention scenarios. This study presents a Light Detection And Ranging (LiDAR) informed, GIS-based decision-support workflow for forest drainage maintenance and modernisation. The workflow integrates automated ditch detection from airborne laser scanning (ALS) derived digital elevation models (DEMs), cross-section-based morphometric assessment of ditch depth and continuity, scenario modelling of ditch restoration, reconstruction and new alignment based on terrain-driven flow patterns, planning of shallow surface drains (remedial ditches) to alleviate seasonal ponding in closed depressions, and cartographic depth-to-water (DTW) screening to quantify expected changes in near-surface wetness. The approach was demonstrated in two forest catchments in the Forest Research Station, northern Latvia, where drainage reconstruction was carried out in 2023–2024 and independently verified with UAV LiDAR acquired after intervention. Agreement between DEM-detected and cadastre-recorded ditch networks reached 90-95% in forest lands, with a practical detectability threshold of 0.3 m ditch depth. Scenario modelling indicated that the modelled ditch network length closely matched the actually reconstructed length (differences of + 0.3 km and -0.29 km in the two catchments), and DTW screening showed a more than twofold reduction of areas with groundwater proximity below 0.3 m in the wetter catchment. Explicit mapping of ditch length and derived ditch-area fractions provides an operational pathway to improve representation of drainage features in greenhouse gas accounting consistent with IPCC Wetlands Supplement methodology. The workflow is implemented as reproducible QGIS Processing tools for drainage and remedial ditch planning.

**Keywords:** LiDAR, digital elevation model, drainage ditches, decision support, depth-to-water modelling.

## Introduction

Artificial drainage is a defining legacy of many boreal and hemiboreal forest landscapes, where ditch networks were constructed to lower groundwater levels, improve soil aeration and trafficability, and increase stand productivity on seasonally waterlogged mineral soils and peat soils. After decades, however, a substantial share of these networks no longer functions as originally designed because of sediment infilling, vegetation encroachment, local subsidence, and disturbances that interrupt hydraulic continuity. As a result, drainage maintenance and modernisation has become a decision problem rather than a routine operation: interventions must be targeted to segments where restoring conveyance meaningfully changes wetness patterns, avoids unnecessary hydrological connectivity, and meets operational and environmental constraints.

The need for objective prioritisation is strengthened by the close coupling between water-table regime and ecosystem processes. On drained peat soils, greenhouse-gas (GHG) fluxes respond strongly to depth-to-water, with methane ($CH_4$) generally declining as the groundwater table is lowered, while carbon dioxide ($CO_2$) emissions from peat decomposition can increase, and the net balance depends on site fertility and long-term hydrological conditions [1]. Drainage planning also has a direct accounting dimension because ditches themselves can act as $CH_4$ emission hotspots; global synthesis indicates that ditch emissions can partially offset methane reductions attributed to peatland drainage, and that the magnitude of this offset varies by climate zone and land use [2]. In parallel, drainage operations can intensify lateral export of dissolved organic carbon and contribute to freshwater browning, making headwater-scale hydrological connectivity a relevant screening criterion for maintenance actions [3]. From a reporting and mitigation perspective, the IPCC Wetlands Supplement explicitly recognises drainage ditches as emission-relevant land features, implying that spatially explicit information on ditch extent and condition can improve GHG estimation consistency and uncertainty management [4].

LiDAR, a remote sensing technology that measures distances by emitting laser pulses and recording their return times, enables sub-metre terrain reconstruction over large areas and has become the primary data source for operational terrain analysis in countries with national scanning programmes, including Latvia [5]. Airborne laser scanning (ALS) provides a strong basis for operational decision support because LiDAR-derived digital elevation models (DEMs) resolve microtopography at sub-metre scale across large areas. This enables ditches to be detected as elongated concave features and supports morphometric characterisation (e.g., depth, cross-sectional form, continuity) from DEM-derived profiles. Methods for automated ditch extraction have progressed from terrain-index thresholding and object-based delineation approaches, demonstrated in wetlands using LiDAR-derived terrain models [6] to supervised learning that combines multiple terrain attributes to improve detection under forest canopy [7]. More recently, deep learning approaches have been explored for terrain-driven detection tasks, indicating further potential to improve generalisation across heterogeneous landscapes and to reduce manual post-processing in complex hydro-geomorphic settings [8]. However, drainage maintenance requires more than "presence or absence" mapping: practitioners need interpretable indicators of technical condition (e.g., partial infilling versus loss of trace), functional connectivity, and plausible alignments for restoration or redesign.

Hydrological context is therefore essential. Ditch segments differ in contributing area, network position, and connectivity to natural channels; consequently, their maintenance has different hydrological effects and different implications for downstream water quality. In boreal catchments, ditching can substantially increase effective channel length and hydrological connectivity, highlighting the importance of prioritising interventions that deliver operational benefit while avoiding unnecessary connectivity in sensitive areas [9]. A complementary requirement is to quantify how proposed ditch networks may change near-surface wetness. Topography-based wetness indices, particularly the cartographic depth-to-water (DTW) approach, provide a practical way to model spatial patterns of shallow groundwater proximity from DEMs and derived flow networks, and they have been shown to perform well for wet-area mapping relative to alternative terrain indices [10; 11]. DTW-type modelling is attractive for decision support because it can be recalculated under alternative ditch network scenarios (e.g., restored ditches, new alignments), directly linking engineering design choices to predicted wetness patterns relevant to machinery trafficability, operational risk, and biogeochemical "hot spots".

Despite these advances, operational drainage planning still faces two persistent methodological gaps. First, inventories frequently contain "paper ditches" whose current hydraulic function is uncertain; conversely, subtle surface-drain features that influence ponding and seasonal wetness may be absent from inventories. Second, maintenance decisions are inherently scenario-based: the planning problem includes distinguishing partially silted ditches that remain visible in the terrain model from fully silted or missing ditches where new alignment must be proposed based on dominant surface-flow pathways, and where shallow surface drains may be more appropriate than re-establishing full ditch profiles. Engineering-oriented studies emphasise that decision support must integrate detection, condition assessment, and scenario generation in a workflow that remains interpretable and reproducible for practitioners, rather than treating mapping and hydrological modelling as separate analytical exercises [12].

Accordingly, the aim of this study is to develop and demonstrate a LiDAR-informed, GIS-based decision-support workflow for forest drainage maintenance and modernisation that integrates automated ditch detection from ALS-derived DEMs, morphometric assessment of ditch condition and continuity, scenario modelling of ditch restoration versus new alignment based on terrain-driven flow patterns, and DTW-type hydrological screening to quantify expected changes in near-surface wetness patterns relevant to prioritisation and climate-accounting applications.

## Materials and methods

The workflow was demonstrated in two forest catchments within the Mežole Forest Research Station forests in northern Latvia (Catchment A – Lat, Lon 57.2767, 25.8550; Catchment B – 57.3175, 26.0556). Both catchments and analysed ditch networks are located on drained peat soils with an established but partially degraded ditch network. Drainage system reconstruction was carried out in the two catchments during 2023-2024, providing an opportunity for before-and-after comparison. According to the national drainage cadastre (Meliorācijas kadastrs), the registered ditch network totals 2.59 km in catchment A and 11.5 km in catchment B (excluding roadside ditches).

The primary input for this study is the national airborne Light Detection and Ranging (LiDAR) point cloud dataset acquired from the Latvian Geospatial Information Agency (LGIA). The dataset covers the entire territory of Latvia and was collected between 2013 and 2019 at a minimum point density of 4 points m$^{-2}$, with ground-classified returns achieving a minimum density of 1.5 points m$^{-2}$. Vertical accuracy of the survey meets ≤ 12 cm ($2\sigma$, 95% confidence level) and horizontal accuracy ≤ 36 cm (2σ) referenced to the Latvian State Geodetic Network in the LKS-92 TM coordinate system (EPSG:3059) [13]. The methodological framework couples terrain-based drainage ditch feature extraction with their scenario hydrology in a GIS environment. The primary elevation input is an ALS-derived bare-earth digital elevation model (DEM) produced from classified ground points and interpolated to a raster grid suitable for microtopographic analysis (Table 1). To balance the need for detecting narrow linear depressions with the numerical stability of flow-routing, two DEM representations are used: a high-resolution DEM (1 m) for ditch morphometry and a coarser working DEM (2 m) for flow-accumulation and depth-to-water (DTW) modelling, following the logic that wet-area indices can benefit from modest smoothing/resolution increases while retaining topographic control on convergent flow [9].

Table 1

**Core spatial layers and derived products used in the workflow**

| Layer/product | Spatial resolution | Main purpose |
|---|---|---|
| Bare-earth DEM (ALS) | 1.0 m | Ditch detection, cross-sections, ditch depth and condition |
| Flow direction and flow accumulation | 2.0 m | Dominant surface-flow lines; support for re-alignment scenarios |
| Ditch vectors (detected/planned) | poly-line | Network connectivity, prioritisation |
| DTW raster | 2.0 m | Identification of wet areas and change after scenarios |

Prior to hydrological modelling, DEM with 2 m resolution is hydrologically conditioned to reduce artefacts from local pits and road embankments that interrupt downslope connectivity. Conditioning consists of depression handling and explicit enforcement of flow continuity at known crossings (e.g., road–ditch intersections) by locally lowering DEM along culvert locations, thereby preventing unrealistic upstream ponding that would otherwise dominate flow-accumulation patterns. Flow direction and flow accumulation are computed using GRASS GIS *r.terraflow*, which implements scalable flow computation for large grids and outputs flow direction and accumulation rasters used in subsequent DTW calculations and channel-line derivation [14].

A terrain-driven "main surface-flow line" is delineated from the flow-accumulation raster by applying an accumulation threshold (selected to match first-order drainage density at catchment scale) and converting the resulting channel mask to a vector poly-line network. This line is not assumed to be a legal ditch location; instead, it is treated as a geomorphologically plausible alignment for cases where historical ditches are fully silted and no longer expressed as concave micro-terrain.

Ditch detection is performed on the high-resolution DEM with 1 m horizontal resolution using an interpretable, terrain-index–based procedure designed to isolate elongated concave features. Candidate ditch pixels are identified by combining local curvature/concavity descriptors with relative elevation measures computed over a moving window to suppress micro relief noise while retaining narrow incisions. Candidate rasters are then subjected to morphological thinning and converted to vectors, after which short spurs and isolated fragments below a minimum length are removed, based on methodology which is described more in detail in our previous study [15].

Technical condition of ditches is quantified using cross-sections extracted perpendicular to each ditch centreline at a fixed spacing. For each cross-section, the ditch-bed elevation is taken as the minimum elevation within the section, while bank elevation is estimated as the mean (or percentile) of elevations at the outer margins of the cross-section. Ditch depth is then computed as the elevation difference between banks and bed:

$$d = z_{bank} - z_{bed} \tag{1}$$

where $d$ – ditch depth, m;
$z_{bank}$ – representative bank elevation, m a.s.l.;
$z_{bed}$ – ditch-bed elevation, m a.s.l.

Sections are aggregated along each ditch segment to obtain robust segment-level summaries (e.g., median depth, depth variability). A conservative detectability threshold ($d \geq 0.30$ m) is applied to separate ditches that remain morphologically expressed in the DEM from those that are plausibly fully silted. Vegetation encroachment and apparent obstruction are characterised using canopy-height or vegetation metrics where available, but the primary decision variables remain the depth and continuity of the concave trace to preserve method transferability across datasets.

Four scenario types are modelled to reflect typical operational decisions. First, “restoration” targets ditches that remain detectable (depth above threshold) and applies cleaning/reshaping without changing alignment. Second, “reconstruction by trace” targets partially detectable ditches with intermittent expression; gaps are bridged by connecting adjacent detectable reaches while enforcing downslope consistency. Third, “new alignment” targets fully silted or missing ditches; here the proposed centreline follows the dominant surface-flow line derived from flow accumulation, subject to constraints that avoid unrealistic crossings and preserve outlet connectivity. For all main-ditch scenarios (restoration, reconstruction by trace and new alignment), planned ditches are carved into the 2 m DEM as trapezoidal depressions with a representative width of 4 m (matching the 2 DEM cell size) and a design depth of 1.5 m. These dimensions follow standard drainage design practice for forest collector ditches and ensure that the modified DEM reflects a functionally restored cross-section for subsequent DTW computation.

Fourth, remedial ditches (shallow surface drains) target seasonal ponding in closed depressions. Depression locations are identified by applying a sink-filling algorithm to the 2 m DEM and computing the difference between the filled and original surfaces; depression area and depth are recorded for each feature. The deepest point within each depression is located using a maximum-elevation filter in GRASS GIS applied in an inverted sense and converted to a point layer that serves as the starting node for surface-drain routing. Depressions smaller than 0.2 ha and points located beyond a user-defined maximum distance from the nearest ditch or flow-accumulation zone are excluded. Remaining start points are connected to the existing or planned ditch network along the steepest-descent path, and the resulting lines are simplified to a practically realisable surface-drain alignment. Surface drains are carved into the DEM at a representative width of 1 m and depth of 0.4 m. The effect of drain installation is evaluated by repeating the depression identification analysis on the modified DEM and comparing residual ponding area and depth with the baseline.

The DTW index is computed as described by Murphy et al. [10] and Ågren et al. [11], where the full algorithmic formulation is described in detail. In our workflow, DTW is calculated for the baseline ditch network and recomputed for each scenario after updating the channel layer with detected and/or planned ditches and surface drains. Areas with DTW < 0.30 m are classified as wet and the areal fraction below this threshold is used as the primary indicator of scenario effect.

Ditch detection accuracy was assessed against the national drainage cadastre (Meliorācijas kadastrs), which records the location and length of registered drainage infrastructure. Agreement was quantified as the proportion of cadastre-recorded ditch length that was also detected in the DEM at the minimum depth threshold (≥ 0.3 m), evaluated separately for agricultural land and forest land.

To validate post-intervention geometry, a UAV LiDAR survey was conducted in November 2024, after the end of the vegetation season, using a DJI Zenmuse L1 laser scanner mounted on a DJI Matrice 300 RTK platform [16]. The survey achieved a point density of approximately 160 points $m^{-2}$, from which a new DEM was generated for both catchments. The ditch detection and DTW modelling workflow was then re-applied to the post-intervention DEM, and results were compared with the modelled (pre-intervention scenario) and actually reconstructed ditch layouts to assess how closely the terrain-based planning matched implemented works.

The workflow is operationalised as QGIS Processing tools implemented in Python (PyQGIS) to support reproducible execution, parameter logging, and scenario batch runs directly in the users GIS environment. Tool development follows the QGIS Processing framework for algorithm providers and scripting, enabling integration with GRASS modules and native raster/vector processing [17].

To enable screening of ditch-related $CH_4$ accounting, ditch length is converted to ditch area using an assumed mean ditch width from obtained ditch polygons. The ditch fraction can be used to parametrise ditch contributions in land based GHG accounting consistent with the IPCC Wetlands Supplement logic for drained organic soils and associated features, recognising that ditches can be emission-relevant elements requiring explicit representation when data allow [4].

## Results and discussion

Automated extraction from the LiDAR-derived DEM produced a spatially coherent ditch network in both open and forested terrain, with performance constrained primarily by ditch expression in microtopography rather than by catchment size. Agreement with independent reference data reached 96% in agricultural land and 90-95% in forest land when evaluated by length-based matching, indicating that the approach is robust under canopy cover provided that the bare-earth DEM retains sufficient local relief. A practical minimum detectable ditch depth of approximately 0.3 m emerged from the cross-section analysis: below this threshold, concave signatures became intermittent and segmentation errors increased, whereas deeper ditches were mapped continuously and with fewer spurious branches.

Ditch technical condition metrics derived from DEM cross-sections showed high within-network heterogeneity. Depth distributions were typically right-skewed, with a substantial fraction of reaches clustering near the detectability limit, consistent with progressive infilling and partial loss of hydraulic capacity. In practical terms, this enabled a separation into (i) clearly expressed ditches suitable for maintenance/restoration along the existing trace and (ii) fully silted or missing ditches for which alignment had to be re-derived from terrain-driven flow convergence. The connectivity classification further highlighted that local interruptions at crossings (e.g., roads) can dominate the apparent fragmentation of the network unless explicitly conditioned, justifying the inclusion of culvert enforcement during DEM conditioning.

Scenario modelling demonstrated that restoration and redesign decisions materially change the predicted wet-area extent. In catchment A, the drainage cadastre records 2.59 km of ditches, of which only 0.78 km were detectable at the ≥ 0.3 m depth threshold, implying that 1.81 km of the registered network was fully silted or otherwise non-functional at the time of LiDAR acquisition. In catchment B the discrepancy was even larger: 11.5 km registered versus 4.65 km detected. Terrain-based scenario modelling indicated that 4.63 km of ditches needed to be created or restored in catchment A and 5.74 km in catchment B. Comparison with the post-intervention UAV LiDAR DEM showed that the actually reconstructed network totalled 4.93 km in catchment A and 5.45 km in catchment B, corresponding to differences of +0.30 km and -0.29 km relative to the modelled requirement, respectively (Fig. 1).

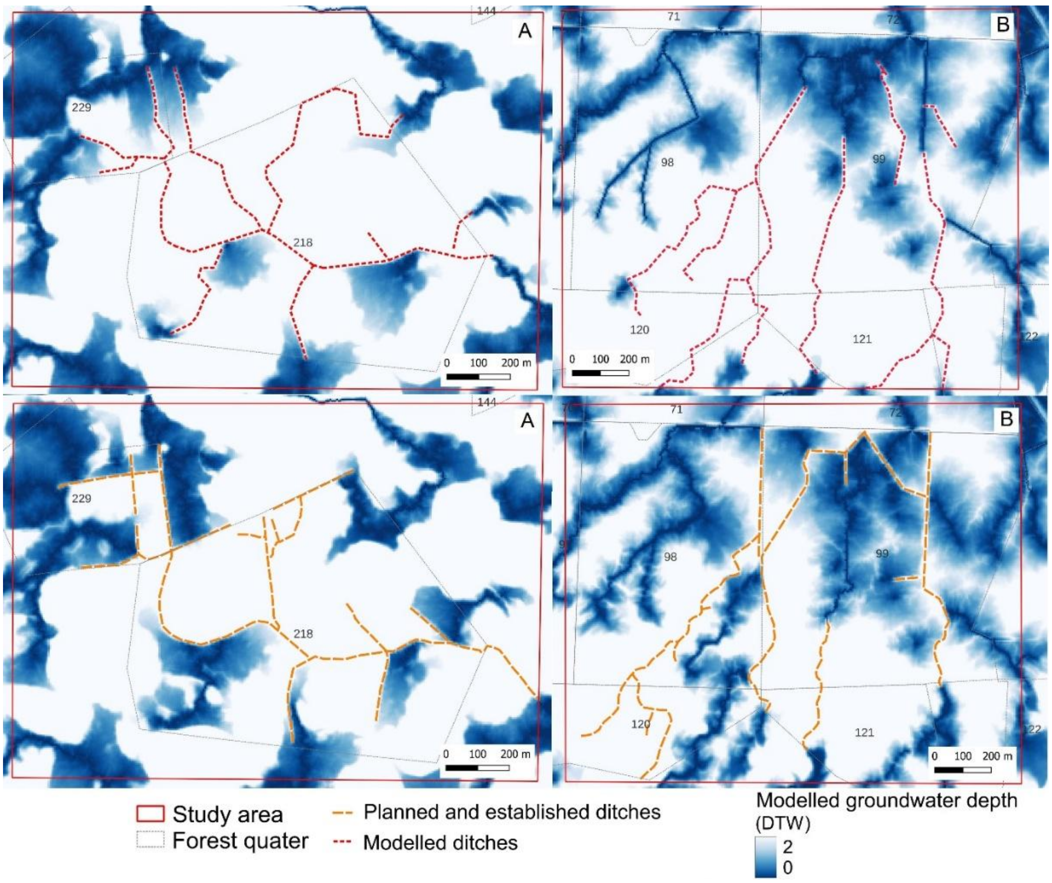


Fig. 1. **Planned and modelled drainage ditches and respective DTW values in study sites**

This close correspondence supports the practical utility of flow-accumulation-based alignment as a planning tool.

DTW screening was sensitive to scenario choice. In catchment A, mean DTW increased from 3.1 m (baseline) to 4.4 m (modelled scenario) and 4.1 m (actual post-reconstruction), and the areal fraction with DTW < 0.30 m declined by more than twofold under both scenarios. In catchment B, mean DTW increased from 1.3 m to 3.2 m (modelled) and 2.2 m (actual), but the reduction in wet-area extent was less pronounced, indicating diminishing hydrological returns in the already wetter catchment where topographic convergence limits the drainage effect. The difference between the modelled and actual DTW outcomes (4.4 vs 4.1 m in A; 3.2 vs 2.2 m in B) reflects the fact that actual ditch depths and alignments do not perfectly replicate the uniform design assumptions of the model.

The surface-drain (remedial-ditch) planning tool was applied in both catchments. Depression analysis on the baseline DEM identified closed depressions exceeding 0.2 ha that were not connected to the ditch network. After carving the modelled surface drains into DEM and repeating the depression analysis, residual ponding area was reduced in both catchments, confirming that the routing algorithm successfully connected isolated depressions to the nearest collector ditch. Quantitative evaluation of depression count, area and depth change before and after surface-drain insertion will be reported in a follow-up study together with field verification of drain performance.

A by-product of the workflow is an explicit estimate of ditch area and its spatial distribution. When converted from length using representative design widths, ditch-area fractions differed substantially between baseline and scenario networks, implying that ditch-related $CH_4$ terms in landscape GHG accounting can change meaningfully when maintenance modernises the network rather than simply cleaning existing lines. This provides an operational pathway to move beyond uniform ditch fractions by site type and to support catchment-specific screening of climate co-benefits.

Table 2

**Summary of key performance and scenario outcomes**

| Metric/outcome | Result (range) |
|---|---|
| Practical minimum detectable ditch depth | 0.3 m |
| Example mismatch: inventory vs detectable ditches | 2.59 km vs 0.78 km (depth ≥ 0.3 m) |
| Change in wet area (DTW < 0.30 m) in wetter catchment | > 2-fold reduction |

The observed mapping performance is consistent with the broader literature showing that LiDAR-based ditch detection can achieve high accuracy when DEM preserves ditch-scale concavity and when feature extraction is coupled to appropriate terrain descriptors and post-processing. Supervised learning applied to LiDAR DEMs has similarly been shown to detect ditches effectively, especially where training data capture variability in land cover and ditch morphology [7]. The key operational insight from the present results is that detectability is governed by a depth threshold on the order of decimetres: once ditches are close to being levelled by sedimentation, the geomorphic signal becomes too weak to reliably distinguish from natural microtopography and DEM noise. This reinforces the need to treat "non-detection" not merely as an algorithmic error but as a diagnostic indicator of functional degradation that can be prioritised for field checks and redesign planning.

DTW-based screening behaved in line with prior evidence that depth-to-water indices provide a practical representation of wetness gradients relevant to forestry operations and ecological patterns, often outperforming or complementing conventional wetness indices [10]. The strong reduction in DTW-defined wet areas in the wetter catchment supports the conceptual link between restoring drainage connectivity and lowering the spatial footprint of near-surface water tables, although the smaller response in the drier catchment illustrates that returns saturate when topographic convergence is limited or when drainage density already exceeds the threshold for effective groundwater control. This is consistent with findings that DTW performance and wet-area delineation can be relatively insensitive to modest changes in DEM resolution within the 0.5-2.0 m range, but can be sensitive to threshold selection and local transmissivity conditions [18]. Consequently, DTW is best interpreted here as a comparative scenario tool rather than an absolute predictor of groundwater depth, supporting prioritisation, where will wetness decrease most, rather than deterministic compliance assessment.

From a climate-accounting perspective, explicit ditch mapping and scenario-dependent ditch-area fractions are increasingly important because drainage ditches can be substantial $CH_4$ sources that partially offset methane reductions associated with wetland drainage at broader scales [2]. The IPCC Wetlands Supplement provides methodological guidance for drained organic soils and explicitly recognises that ditches can be relevant components for GHG estimation, motivating improved spatial characterisation where operational data permit [4]. The workflow presented here supports this need by generating spatially explicit ditch metrics that can be coupled to emission-factor approaches and uncertainty analysis, while also enabling mitigation screening: interventions that substantially reduce persistent wet patches may reduce $CH_4$ risk in saturated microsites, but network expansion may simultaneously increase the ditch area and thus potential ditch $CH_4$ emissions. The net effect is therefore site- and design-specific, strengthening the case for scenario evaluation rather than generic assumptions about drainage impacts.

The remaining limitations are primarily structural. DTW outcomes are sensitive to within-network heterogeneity in ditch depth and to local bottlenecks (e.g., partially blocked crossings), which are not fully represented when scenarios apply uniform design depths or when culvert status is uncertain. In addition, fully silted ditches may be absent from DEM, so alignment derived from flow accumulation is a geomorphically plausible but not necessarily optimal engineering solution where constraints (ownership boundaries, protected habitats, soil bearing capacity) dominate. These constraints motivate the next development steps: integrating field or UAV derived depth controls for calibration, incorporating rule-based constraint layers into alignment optimisation, and formalising uncertainty propagation from ditch depth variability into DTW and downstream GHG screening.

## Conclusions

1. A LiDAR-GIS decision support workflow can map and characterise forest drainage networks with high agreement to reference data and to identify ditches which need reconstruction, enabling operational scale screening of drainage maintenance needs without exhaustive field surveying.
2. A practical detectability threshold of ditch depth around 0.3 m separates morphologically expressed ditches suitable for maintenance along existing traces from fully silted or missing structures that require re-alignment planning; thus, non-detection in DEM derived products can be interpreted as an indicator of functional degradation rather than solely a mapping error.
3. Cross-section based morphometry provides spatially explicit indicators of ditch technical condition and connectivity, supporting prioritisation by identifying fragmented reaches and bottlenecks where restoring continuity is likely to yield disproportionate hydrological benefits.
4. Scenario modelling that combines restoration of detectable ditches with terrain driven alignment for non-detectable segments yields measurable changes in near-surface wetness patterns; DTW screening indicates the largest benefits in wetter catchments, including > 2-fold reductions in areas with DTW < 0.30 m, while responses are smaller and more localised in drier catchments, implying diminishing returns of network expansion.
5. Explicit mapping of ditch length, depth classes and derived ditch-area fractions provides a practical pathway to improve representation of drainage ditches in spatially resolved GHG screening consistent with IPCC Wetlands Supplement logic, while highlighting that net climate effects are site- and design-dependent because reduced wet-area extent may coincide with increased ditch area.
6. Key limitations arise from sensitivity of DTW outcomes to ditch depth heterogeneity, uncertain crossing structures, and the fact that flow-accumulation based traces are geomorphically plausible but not fully constrained by engineering, ecological, and legal requirements; future development should integrate field and UAV calibration, constraint layers for alignment optimisation, and uncertainty propagation from ditch condition metrics into wetness and GHG indicators.

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**Author contributions**

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