Digital Wet Areas Mapping

William Lidberg
Faculty of Forestry
Department of Forest Ecology and Management
Umeå

Doctoral thesis
Swedish University of Agricultural Sciences
Umeå 2019

Acta Universitatis agriculturae Sueciae

2019:10

Cover: Krycklan by Veija 4 years and Vinston 2 years
(Art by Jenny Johansson)

ISSN 1652-6880
ISBN (print version) 978-91-7760-338-2
ISBN (electronic version) 978-91-7760-339-9

Print: SLU Service, Uppsala 2019

Digital Wet Areas Mapping

Abstract

Wet soil in forested landscapes of the boreal zone is often associated with large open wetlands or peatlands, but it may also be hidden beneath closed forest canopies on drained wetlands or wet strips beside streams known as riparian zones. Since these wet areas are shrouded by canopy they have traditionally been difficult to map from aerial photographs. Consequently, most of them are not marked on current maps. Movements of heavy forestry machines can severely disturb the soil and impair water quality in these wet and moist environments, so driving should be avoided in them. However, to avoid driving and plan forestry operations in these areas it is important to know where they are. Therefore, the aim of the studies this thesis is based upon was to evaluate and develop methods to map these hidden streams and wet areas so they can be considered in forestry planning to minimize negative effects of forestry on soil and water quality. High resolution digital elevation models (DEMs) are becoming more accessible as more countries are conducting laser scanning campaigns, and hydrological features such as streams and wet areas can now be topographically modelled on large scales. Stream networks extracted from these high resolution models are more accurate than current stream networks, provided that appropriate methods are used to pre-process the DEM. Forest-covered wet areas can also be mapped using DEMs, but no currently available method is universally applicable. Therefore my colleagues and I used machine learning to combine stream networks acquired using multiple methods with other soil and climate maps to more accurately predict wet areas. The new maps generated in this manner are relatively cheap to produce and can be used to plan forestry operations in great detail. Protective buffer zones can be placed around previously unknown headwater streams and these maps can be used to avoid driving in sensitive areas with heavy forestry machines.

Keywords: Light detection and ranging, Wet areas mapping, Digital elevation model, GIS, riparian zone, streams, forestry, Buffer zone

Author's address: William Lidberg, SLU, Department of Forest Ecology and Management,
P.O. 901 83 Umeå, Sweden

Markfuktskartering

Sammanfattning

Fuktig mark i det boreala skogslandskapet associeras ofta med stora öppna myrar men blöt och fuktig mark finns även gömd i skogen som dikade myrar eller längs med vattendrag. Eftersom dessa områden är täckta av skog så har de varit svåra att kartlägga från flygbilder. Ett resultat av det är att de flesta vattendragen och fuktiga markerna saknas på dagens kartor. Fuktiga marker är känsliga för körskador från tunga skogsmaskiner och körning bör därför undvikas i dessa områden. Men för att kunna planera skogsbruk och undvika körskador på fuktig mark så måste man först veta var den fuktiga marken finns. Därför var syftet med den här avhandlingen att utvärdera och utveckla metoder för att hitta små vattendrag och fuktig mark så de kan inkluderas i den skogliga planeringen för att minska skogsbrukets negativa effekter på sjöar och vattendrag. Högupplösta höjdmodeller blir vanligare allteftersom fler länder genomför luftburna laserskanningar som kan användas för modellering av hydrologiska objekt som vattendrag och fuktig mark på stor skala. Vattendrag modellerade från högupplösta höjdmodeller har en högre träffsäkerhet än dagens kartor förutsatt att höjdmodellen har förberetts på rätt sätt. Fuktig mark som ligger gömd i skogen kan karteras men det finns inte en metod som fungerar överallt. Istället använder vi maskininlärning för att kombinera flera olika metoder med befintliga jordarter och klimatdata för att prediktera markfukt med hög träffsäkerhet. Kartorna är relativt billiga att producera och kan användas för att i detalj planera skogsbruk nära vatten. Skyddande kantzoner kan planeras runt tidigare okända vattendrag och körning av stora maskiner kan planeras så att skador på de känsliga markera undviks.

Nyckelord: Markfuktskarta, digital höjdmodell, geografiska informationssystem, skyddszon, vattendrag, skogsbruk

Författarens adress: William Lidberg, SLU, Institutionen för skogens ekologi och skötsel,
P.O. 901 83 Umeå, Sverige

Dedication

To Jenny, Veija and Vinston.

42

Deep Thought

Contents

List of publications

This thesis is based on the work described in the following articles, which are referred to by corresponding Roman numerals in the text, and sometimes the studies that Articles I-IV are based upon are referred to as Studies I-IV, for convenience.:

I William Lidberg*, Mats Nilsson, Tomas Lundmark, Anneli M. Ågren (2017). Evaluating pre-processing methods of digital elevation models for hydrological modelling. *Hydrological Processes*, 31 (26), pp. 4660-4668.

II Ågren, A. M. and Lidberg*, W.: The importance of better mapping of stream networks using high resolution digital elevation models – upscaling from watershed scale to regional and national scales, *Hydrol. Earth Syst. Sci. Discuss*., https://doi.org/10.5194/hess-2019-34, in review, 2019.

III William Lidberg*, Mats Nilsson, Anneli M. Ågren (2019) Using machine learning to generate high resolution wet area maps for planning forest management: a study in a boreal forest landscape. *Manuscript Submitted to Ambio.*

IV William Lidberg*, Mats Nilsson, Erik Emilson, Irena Creed, Anneli M. Ågren (2019). Mapping riparian zones using digital elevation models. *(manuscript)*

Articles I-III are reproduced with the permission of the publishers.

* Corresponding author.

Other related publications

1. Jason Leach, William Lidberg, Lenka Kuglerova, Andress Peralta-Tapia, Anneli M. Ågren, Hjalmar Laudon (2018). Evaluating topography-based predictions of shallow lateral groundwater discharge zones for a boreal lake-stream system. *Water Resource Research, 47 (7), pp. 546-556.*

2. Eliza Maher Hasselquist, William Lidberg, Ryan A Sponseller, Anneli M. Ågren, Hjalmar Laudon (2017). Identifying and assessing the potential hydrological function of past artificial forest drainage. *Ambio*, 53 (7), pp. 5420-5437.

3. Tejshree Tiwari, Fredrik Lidman, Hjalmar Laudon, William Lidberg, Anneli M. Ågren (2016). GIS-based prediction of stream chemistry using landscape composition, wet areas and hydrological flow pathways: Modeling biogeochemistry. *Journal of Geophysical Research: Biogeosciences*, 122 (1).

4. Anneli M. Ågren, William Lidberg, Eva ring (2015). Mapping temporal dynamics in a forest stream network - implications for riparian forest management. *Forests*, 6 (9), pp. 2982-3001.

5. Anneli M. Ågren, William Lidberg, Monika Strömgren, Jae Ogilvie, Paul Arp (2014). Evaluating digital terrain indices for soil wetness mapping–a Swedish case study. *Hydrology and Earth System Sciences*, 18 (9), pp. 3623-3634.

The contribution of William Lidberg to the articles included in this thesis was as follows:

I Idea and hypothesis 40 %, planning and performance of work 90 %, analysis and summary of results 100 %; writing of manuscript 90 %

II Idea and hypothesis 40 %, planning and performance of work 50 %, analysis and summary of results 30 %; writing of manuscript 50 %

III Idea and hypothesis 80 %, planning and performance of work 100 %, analysis and summary of results 100 %; writing of manuscript 80 %

IV Idea and hypothesis 50 %, planning and performance of work 90 %, analysis and summary of results 100 %; writing of manuscript 90 %

Abbreviations

ANN	Artificial Neural Network
D8	Deterministic 8
DEM	Digital Elevation Model
DRIP	Discrete Riparian Inflow Point
DTW	Depth to Water
EAS	Elevation Above Stream
LiDAR	Light Detection and Ranging
ML	Machine Learning
MLWAM	Machine Learning Wet Area Map
NB	Naïve Bayes
NFI	National Forest Inventory
NILS	National Inventory of Landscapes in Sweden
RF	Random Forest
SVM	Support Vector Machine
TWI	Topographic Wetness Index
WFD	Water Framework Directive

1 Introduction

The European Union's Water Framework Directive (WFD) entered into force in 2000 with the purpose to protect water in Europe, thereby improving its ecological health and cleanliness. This directive is ambitious legislation, encompassing ecological and chemical protection of both groundwater and surface waters. It applies to all waters in the European Union. There have been many problems in implementation of the WFD (Voulvoulis et al. 2017), but one of the biggest issues was somewhat unexpected: no one seems to know where the water is. Lakes and rivers are well documented, but most headwater streams are not included in any databases and monitoring programs. However, they do exist and Bishop et al. (2008) even refer to them as "*Aqua Incognita*", a fitting name since most of them are not even marked on maps. Maps have traditionally been constructed from aerial photos (Bird et al. 2010), but small stream channels are difficult to observe from the air, especially under a dense tree canopy. Hence, maps generally display large streams, and streams in agricultural areas where trees are scarce, while many smaller streams, especially in forested areas, are missing (Jensen et al. 2017). Thus, lengths of stream networks based on current maps will be severely underestimated (Elmore et al. 2013). This hinders both rational management and research efforts, such as attempts to elucidate ecological processes and carbon budgets (Kuglerová et al. 2017).

A further complication is that the missing headwater streams are at the interface between soil and water. They start from wet patches only visible from differences in vegetation and eventually form trickles on the surface of the soil. This is where groundwater becomes surface water, and the resulting network of small streams eventually merges with other streams that contribute to rivers and lakes. Headwater streams have high edge to surface areas (Richardson and Danehy 2007), and it's in this capillary network that water meets soil and the two phases interact with each other, in a similar manner to the gas (largely oxygen and carbon dioxide) exchange between the atmosphere and blood in capillaries in our lungs. However instead of transporting oxygen from our lungs these headwaters transport various inputs from soils in the surrounding landscape into downstream ecosystems (Klaminder et al. 2006; Rosemond et al. 2015; Lidman et al. 2017). Interactions between headwater streams, surrounding landscapes and the ecosystem services they provide have been intensively studied (de Sosa et al. 2018). Riparian zones are key habitats for many species of invertebrates, amphibians and plants, and they are often used as dispersal corridors (Clarke et al. 2008) (Figure 1). Riparian zones also accumulate high levels of organic matter, which impact biogeochemical processes during their transport from terrestrial to aquatic environments. Water table fluctuations, and accompanying shifts in redox conditions, in riparian soils may promote elevated rates of net mineralization and export of nitrogen (Blackburn et al. 2017). Trees in the riparian zone also provide shading for streams that keeps temperatures down, which is crucial for the survival and reproduction of many aquatic organisms (Luke et al. 2007).

Figure 1: Example of the riparian zone along a headwater stream in the boreal zone. The image was taken in the Noarralån catchment during field work in the study reported in Article I. A small stream running through the centre of the scene is surrounded by grass and shrubs on both sides.

Like headwater streams, there are large areas of unmapped wet soils in the boreal zone. Open peatlands are recognisable features in the boreal landscape, and like streams they have been mapped from aerial photographs. However, wet soils also occur on tree-covered peatlands and in the riparian zones of forest streams or surrounding lakes. Creed et al. (2003) coined the term "cryptic wetlands" for forested areas of wet soils that are missing from current maps. These could be natural wetlands or mires that have been ditched to increase forest productivity (Hasselquist et al. 2017). Initial comparisons with field data suggest that only

36% of soil classified as wet or moist is shown on current topographical maps of Sweden. This has become problematic, especially for forestry operations, as wet and moist soils have lower bearing capacity than dry soils (Cambi et al. 2015) and are more susceptible to disturbance (Mohtashami et al. 2017).

Mercury and lead also tend to bind to organic matter. Munthe and Hultberg (2004) recorded a three-fold increase in MeHg concentrations in runoff after a forest machine caused soil damage near a stream in northern Sweden. The elevated MeHg levels remained in following years, demonstrating that forestry activities that cause soil damage in the riparian zone can mobilise the mercury pool that has accumulated in soil from atmospheric deposition. Forestry operations can also mobilise nutrients by promoting nitrogen mineralization and nitrification (Kreutzweiser et al. 2008), thereby increasing nutrient export to streams and downstream environments (Laudon et al. 2016) and eventually coastal waters (Futter et al. 2010). Soil damage in the riparian zone can also lead to erosion from ruts, followed by sediment deposition and burial of important spawning habitats (Kreutzweiser and Capell 2001).

Forested buffer zones and machine-free areas near streams and lakes are commonly used to protect surface water during forestry activities, but current management practices vary between countries due to differences in legislation (Ring et al. 2017), and fixed width buffers of 1-30 m are commonly used. In Ontario, Canada, the guidelines recommend >30 m on each side of streams, but there are no buffer requirements for streams without fish or <1.5 m wide in British Columbia, Canada (Kuglerová et al. 2017). Swedish guidelines recommend that forested buffers should be maintained along small headwater streams while intermittent streams are often left without buffers (Kuglerová et al. 2014b). Fixed width buffers are easy to plan and implement for managers and provide some protection, but are criticized since they are normally tree-covered strips with uniform age structure and width that do not take small-scale variations into account (Richardson et al. 2012). Leaving a fixed width of uncut forest can also have negative effects since some ecosystems are reliant on some periodic disturbance (Kreutzweiser et al. 2012). Some of this natural disturbance can be emulated by taking small-scale hydrological features into account during harvesting. Groundwater generally follows surface topography of compacted glacial till soils (Bishop et al. 2011) and converges in valleys, and as these valleys lead towards the riparian zone they create Discrete Riparian Inflow Points (DRIPs) (Ploum et al. 2018). Using temperatures recorded by distributed sensors and water isotope composition measurements along a 1500 m headwater stream Leach et al. (2017) showed that topography-based predictions of DRIPs are generally accurate. Further, Kuglerová et al. (2014a) showed that this local groundwater input increased vascular plant species richness between 15 % and

20 %, possibly by increasing soil pH and nitrogen availability. Moreover, this relationship between groundwater discharge and plant species richness was observed from zero-order basins to a seventh-order river (Kuglerová et al. 2014a). Riparian zones play an important role in regulating water quality at small spatial scales due to this connection with biogeochemical sources in upland soils. In addition, Tiwari et al. (2016) found that hydrologically adapted buffers included more wetlands and low-productivity forest areas than fixed width buffers, concluding that they are cheaper per unit area.

However, implementing these protective measures in practice can be complicated due to deficiencies of available planning tools. For example, Ågren et al. (2015) found that, depending on the season, 58 % to 76 % of all streams were not marked on maps of a studied catchment in northern Sweden. In addition, streams that are present on current maps are often incorrectly placed, and some streams shown on the maps do not exist. Without accurate maps of streams and wet soils it is difficult for managers to plan protective measures such as buffer zones (Laudon et al. 2016; Kuglerová et al. 2017) and off-road driving with forestry machines (Ågren et al. 2015). A solution for this problem is to use topographical models to extract hydrological features from digital elevation models (DEMs). This is by no means a new approach, for example deriving Topographic Wetness Index (TWI) values in this manner, as initially described by Beven and Kirkby (1979), has been a popular approach for mapping wet areas for decades. However, recent advances in remote sensing, especially Light detection and ranging (LiDAR) have paved the way for new high-resolution DEMs. Early DEMs were often created by photogrammetry (Figure 2a) while modern DEMs are derived from LiDAR point clouds and can have resolutions of less than 0.5 m x 0.5 m (a grid resolution of 0.5 m x 0.5 m is hereafter written as 0.5 m) (Reutebuch et al. 2003) (Figure 2b). The number of national LiDAR campaigns is growing and new high resolution DEMs generated from them are becoming accessible in many countries (van Leeuwen and Nieuwenhuis 2010; Guo et al. 2017).

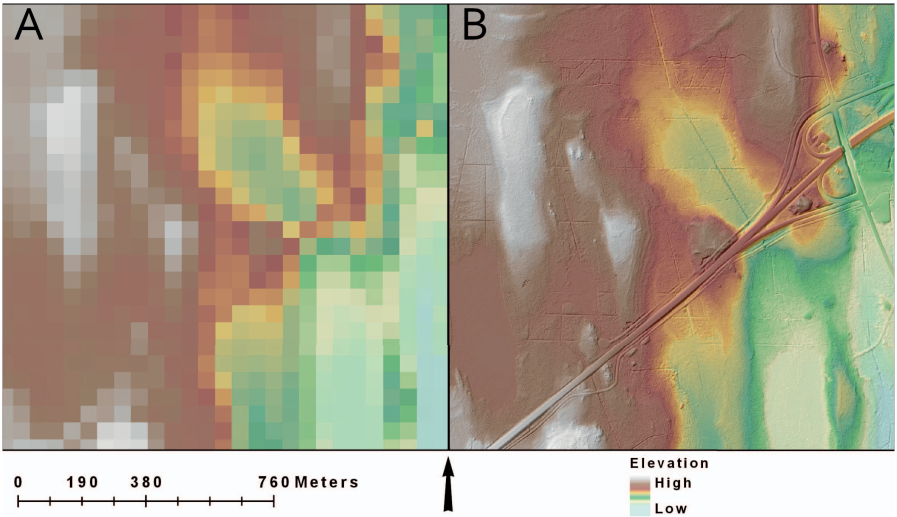

Figure 2. Illustration of differences in detail associated with different DEM resolutions. A) 50 m DEM derived from photogrammetry and B) 2 m DEM derived from LiDAR point clouds. DEM © Lantmäteriet.

High-resolution DEMs are increasing in popularity amongst managers and are often used to map hydrological features (Vaze and Teng 2007). An assumption underlying this approach is that subsurface water flow paths are related to surface topography. This assumption has been shown to be reasonable for some environments (Devito et al. 2005), but it may not be valid in certain environments and under certain conditions (Grayson and Western 2001). For example, terrain-based approaches have been found to work poorly in catchments with extensive bedrock fractures and in arid to sub-humid environments where evapotranspiration dominates the water balance (Devito et al. 2005). Recently glaciated areas of the humid boreal zone have proven to be suitable for this kind of modelling since the till soils are highly compacted and most runoff occurs in the top 30 cm (Bishop et al. 2011). Perhaps the most commonly extracted features are streams, which are normally modelled in a five-step approach (Tarboton et al. 1991; Tarboton 1997) (Figure 3).

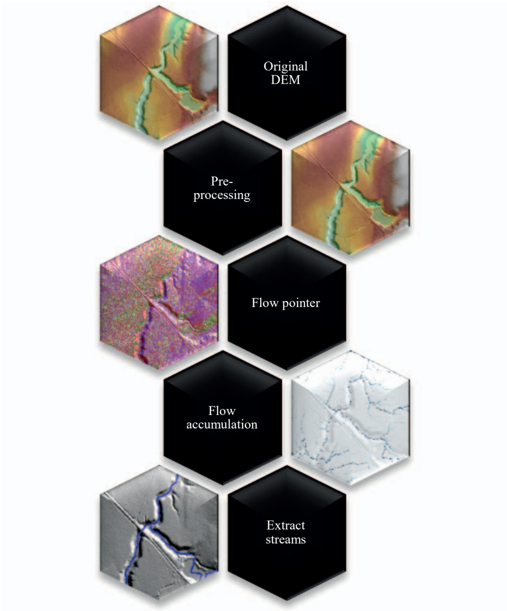

Figure 3. The five basic steps for extracting streams from a digital elevation model (DEM). The original DEM is the only input and it needs to be pre-processed to become hydrologically correct. The corrected DEM is then used to calculate the direction that each cell “flows” and these cells are then summarized in a flow accumulation grid. Once enough cells have accumulated they form a stream. The threshold of accumulated area required varies with climate, soils and topography.

Some advantages of this approach are that modelled stream networks form integrated drainage networks and follow channel depressions (Murphy et al. 2008). However, there are some problems with this approach. The first issue with high resolution DEMs is the sheer amount of data that needs to be processed. Processing time increases dramatically when the resolution increases. An increase in resolution from 2 m to 1 m results in four times more data points to process. Although processing capacities of computer hardware have increased exponentially in the last two decades, this is still challenging for many practitioners. Another issue is that LiDAR scans are conducted from low flying aircraft, and the top-down perspective prohibits distinction between a bridge and a slightly elevated road bank. Similarly, road culverts are not detected, so road banks and bridges will behave like dams and form sinks in a resulting DEM (Figure 4). Sinks are defined as areas of unified lateral flow or internal drainage (O'Callaghan and Mark 1984; Martz and Garbrecht 1998).

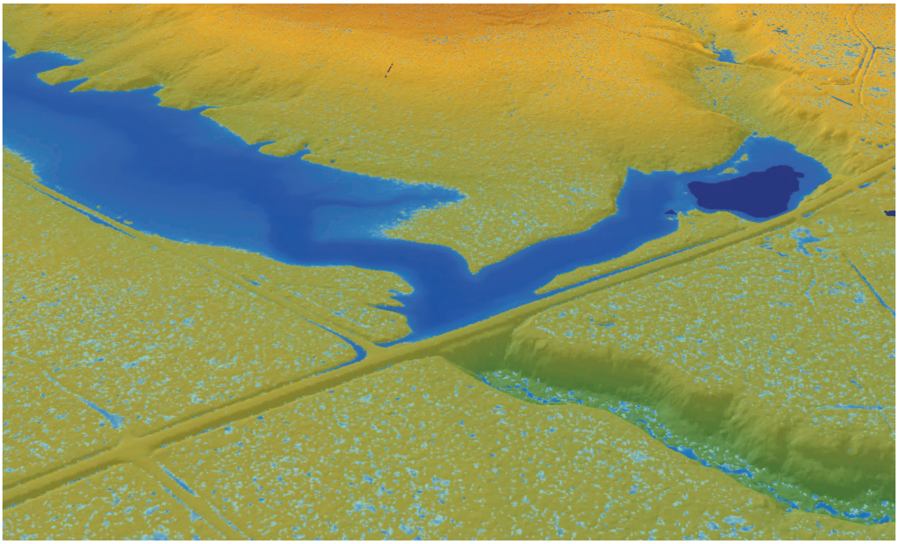

Figure 4. A road causing a sink in a DEM, preventing water from reaching the outlet. In reality, water drains underneath the road in a culvert. DEM © Lantmäteriet.

Before any hydrological modelling can be applied in a DEM it needs to be adjusted to be hydrologically correct (Jenson and Domingue 1988). This step is known as pre-processing and sinks are commonly removed by raising the elevation of cells in the sink to the elevation of surrounding cells to allow water to continue flowing down to the outlet. This approach is known as 'filling' and is the most commonly used method to pre-process a DEM for hydrological modelling. However, if a road crosses a flat area the fill algorithms will fill up the whole area to remove the sink caused by the road embankment, as shown in Figure 4. Another approach is to 'breach' or carve a path across elevated structures by connecting the depression cell with the highest cell on the other side of the bridge by 'burning' a channel across it.

In Sweden there are 570 000 km of roads, equal to 14 times the earth's circumference, and not all roads are concentrated in urban areas. More than 235 000 km of forest roads have been built to extract the timber from 220 000 km^2 of forested land in Sweden alone. Thus, in every km^2 of the forest landscape there is on average ca. 1 km of roads. Ågren et al. (2015) mapped stream networks from a high-resolution DEM and found that for every km^2 there were 2-5 km of streams, depending on the season. This highlights the importance of handling sinks correctly during the pre-processing stage, otherwise resulting hydrologically modelled maps will contain misplaced streams.

As mentioned above, a popular approach for mapping wet areas has been to use the TWI (Beven and Kirkby 1979), but the TWI is sensitive to DEM resolution (Ågren et al. 2014) and the algorithms used to calculate it (Sørensen et al. 2006). Creed and Beall (2009) later built on TWI with Variable Source Area (VSA) to map cryptic wetlands and predict nitrogen export to streams in Canada. Hjerdt et al. (2004) suggested a downslope distance or downslope gradient index, but its use requires catchment-specific thresholds to define wet areas. Wet areas indices based on stream networks, such as Elevation Above Stream (EAS) (Rennó et al. 2008) and Cartographic Depth to Water (DTW) (Murphy et al. 2008a), have already proved to be useful and DTW maps are currently used, for example in Sweden and Canada, to plan forestry operations. However, since they are based on stream networks it is necessary to define a stream initiation threshold, which has proved to be difficult due to temporal dynamics (Ågren et al. 2015), variability in topography and spatial distribution of soils (Ågren et al. 2014). An early attempt to include soil transmissivity in TWI was made by Beven (1986) and more recent attempts include consideration of both soil and climate (Güntner et al. 2004). Most of these topographical methods rely on the user to define appropriate threshold values to define wet areas. Ågren et al. (2014) demonstrated that the optimal flow initiation threshold used to extract DTW maps varied greatly even on a local scale. Soil textures, topography and climatic differences make any application on a large scale difficult (Figure 5).

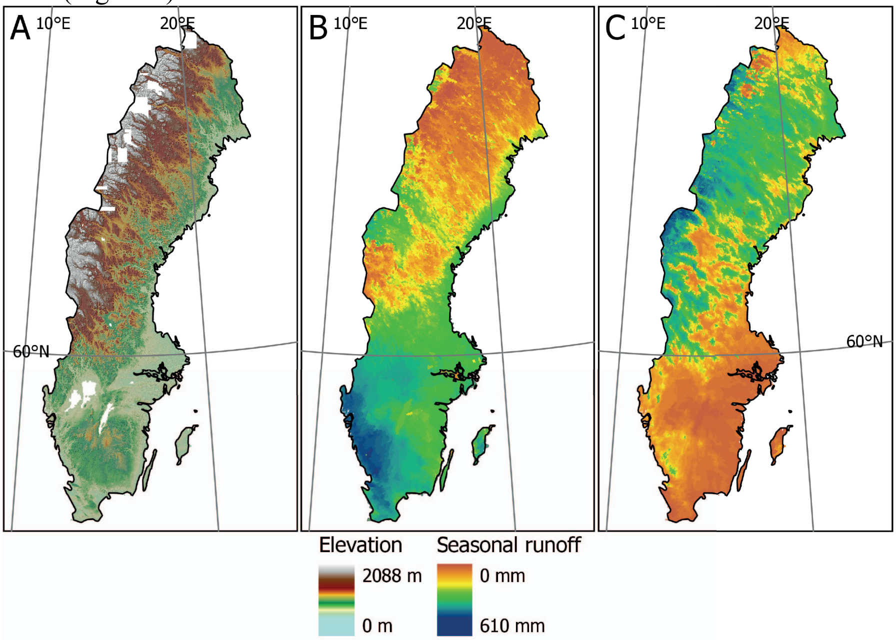

Figure 5: Illustration of the variability of the landscape and climate in Sweden that could affect hydrological modelling, exemplified by: A) The Swedish national DEM, B) Average winter runoff from the last 30 years, and C) Average spring runoff in the last 30 years. DEM © Lantmäteriet and runoff data © SMHI.

2 Research objectives

The overall aim of the work underlying this thesis was to evaluate and develop methods to map streams and wet areas from high resolution DEMs, when scaling up from catchment level to regional and national scales. Such new maps could be used in forestry planning to minimize the negative impact of forestry on soils and water quality. My colleagues and I (hereafter we) addressed a number of practical issues, including the performance of current maps of streams and wet soils. We also used our findings to improve recommendations for forest management near streams and wet areas. More specifically we focused on the following research questions:

- Which DEM resolution should be used to model stream networks and which pre-processing methods can accurately route water across road impoundments at actual culvert locations? (Article I)
- What is the optimum stream initiation threshold for mapping stream networks throughout the Swedish landscape? How accurate are these modelled stream channels in comparison to existing maps of streams? How can the modelling of stream channels be improved by incorporating variability in local topography, soil texture and runoff? (Article II)
- Can machine learning and data from national inventories be used with wet area indices and existing map data to generate more accurate maps of wet soils? (Article III)
- Is it possible to map the riparian zones from high resolution DEMs? Which wet area indices are the best for mapping riparian zones and how accurate are maps based on them? (Article IV)

3 Materials and methods

3.1 Study Site

Most of the work focused on the boreal zone, using field data from Sweden (Articles I, II, III). Sweden is situated in Northern Europe between latitude 55° and 70° N and longitude 11° and 25° E, so most of the country is within the boreal zone. Annual mean air temperatures range from 8˚C in the south to -2˚C in the north (Seekell et al. 2014). The bedrock is mainly composed of Precambrian crystalline rocks, remains of younger sedimentary rock cover and Caledonian mountains in the west. Sweden has been through several glaciations during the last 2-3 million years and most of the quaternary deposits were formed during and after the most recent glaciation, some 22 000 – 10 000 years ago. As a result, 75% of Sweden is covered by glacial till while peat is the second most dominant soil type, covering 13% of the country (Fransson 2018). Glacifluvial sediments were deposited at the ice front during the deglaciation, and isostatic rebound with subsequent wave washing of shores created post-glacial sediments below the highest coast line. According to the Swedish Land Cover database (based on satellite imagery) (Ansen 2004) the main land cover types in Sweden are: forest (63.0%), lakes (8.9%), open mire (8.7%), heathlands (7.7%), arable land (6.1%), forested mire (2.8%), urban area (2.3%), and other (0.6%). However the Swedish National Forestry Inventory (NFI) estimates that 67% of Sweden is forest land (Fransson 2018). Field data from the Black Brook catchment in New Brunswick Canada were also included in Study IV to expand the cover of the boreal zone.

3.2 Field data

It is important to validate computer-generated maps, and in the research underlying this thesis the following field datasets were used to develop and ground-truth the maps. In Article I a rather impressive database of accurately positioned inlets and outlets of 30 883 road culverts in nine large catchments in Sweden was used. In total, the catchments cover 8 350 km^2, of which 82.3, 8.7, 6, 3.8 and 0.3% is forested land, lakes and rivers, open land, agricultural land, and urban areas, respectively (Figure 6).

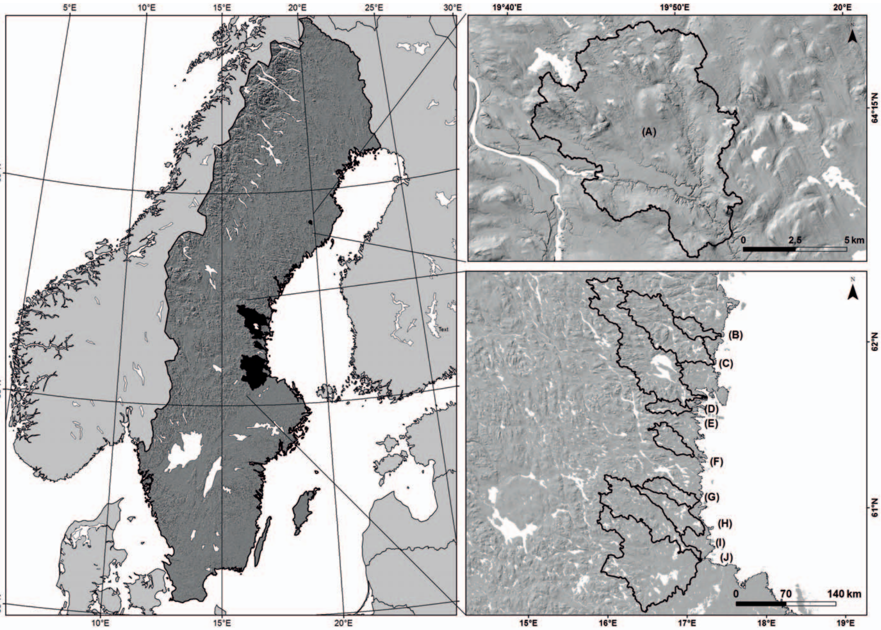

Figure 6: The nine large catchments are located along the coast of central Sweden while Krycklan is 60 km inland in northern Sweden. (A) Krycklan, (B) Gnarpsån, (C) Harmångersån, (D) Delångersån (E) Nianån, (F) Norralanån (G) Skärjån (H) Hamrångeån (I) Testeboån (J) Gävleån. From Article I. DEM © Lantmäteriet.

In Study II, we used the National Inventory of Landscapes in Sweden (NILS) (Ståhl et al., 2011), which provides data on 631 5x5 km squares, systematically distributed throughout Sweden, covering all landscapes (forest, agricultural areas, mountains, wetlands, shores, and cities) (Figure 7a). Data collected from 631 square-shaped line inventories with 200 m line segments, 12 in each square (in total 7 572 segments with a total length of 1 512 km) and 3 323 stream channels narrower than 6 m were mapped.

In Study III, we used estimates of soil moisture from 19 645 permanent field plots included in the Swedish National Forest Inventory (NFI) (Figure 7b)

(Fransson 2018). The NFI includes random sampling of productive forest land (defined as areas with a potential yield capacity of >1 m^3 mean annual increment per ha) and low-productivity forest land (with lower potential yield capacity), for example, peatlands, pastures, areas with thin soils, rock outcrops and areas close to and above the tree-line. However, crop fields, urban areas, roads, railroads, and power lines are excluded from the random sampling. Thus, the registrations of soil moisture provide a good representation of the distribution of soil moisture in landscapes outside urban and arable areas. The NFI plots had a radius of 10 m and were inventoried between the years 2012 and 2016. The GPS accuracy of plots was within 5-10 m and only sites covered by the Swedish National DEM were included (Figure 7b). Average soil moisture conditions in each plot were estimated, based on vegetation patterns and positions in the landscape, then categorized in five classes: dry (6%), mesic (54%), mesic–moist (27%), moist (10%) and wet (3%). As already mentioned, one of the main aims of our research was to facilitate forest management by generating an accurate map to guide off-road driving with heavy machines. Soils classified as wet in the NFI are too wet to drive on unless frozen or using technical aids. While it is possible to drive on moist soils and mesic-moist soils with heavy machinery, it is best to avoid them since they have relatively low bearing capacity. Such soils are readily deformed and displaced, due to their high water and organic contents. Thus there is more soil disturbance and deeper rut formation than in drier more minerogenic dry and mesic soils, where the tracks are shallower (and normally only formed through compaction). Plots in the NFI dataset were therefore divided into two main groups: ‘wet’ and ‘dry’. Plots classified as dry and mesic in the NFI were grouped into the ‘dry’ category (60% of all NFI plots), while those classified as mesic-moist, moist and wet in the NFI were grouped in the ‘wet’ category (40% of all NFI plots). Thus, the ‘wet’ category includes more mesic-moist plots than actual wet plots. Mesic-moist soils are not normally associated with open peatlands or wetlands, but they are defined as soils with a < 1 m deep groundwater table that are unsuitable for trafficking, which is consistent with previously applied criteria for mapping wet areas (Murphy et al. 2008a; Ågren et al. 2014). The underlying rationale is that ‘wet’ soils are more sensitive to rut formation and it is better to move heavy machinery on ‘dry’ soils. To avoid confusion, wet is used hereafter when referring to wet conditions more generally, and ‘wet’ when referring to the wet element of the new binary ‘wet’/‘dry’ grouping described above.

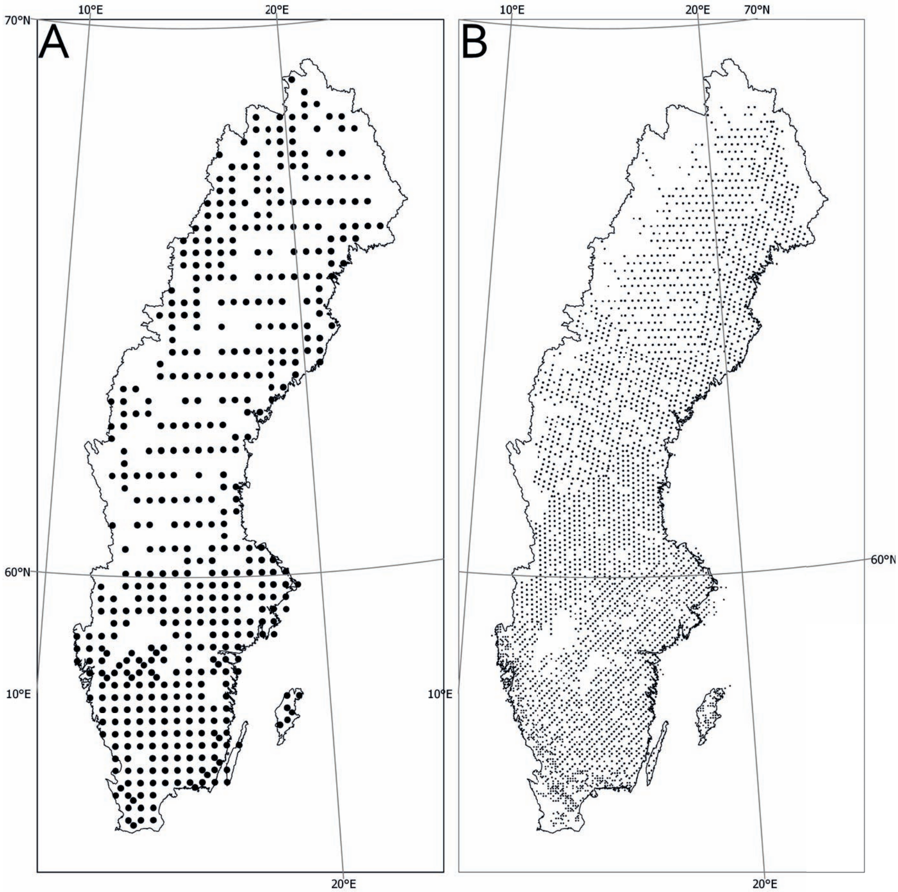

Figure 7: Locations of field sites covered in the NILS database (a) and National Forest Inventory (b) used to obtain data applied in Studies II and III.

In Article IV, we considered field-mapped riparian zones in two catchments in Sweden (Norralaån and Krycklan) and one in Canada (Black Brook). Wet riparian zones were mapped along 36.8 km of streams (25 km in Norralaån, 6.3 km in Krycklan and 5.5 km in Black Brook) using high-precision GPS units. There is significant temporal variability in distributions of wet soils (Ågren et al. 2015), so vegetation communities were used as proxies for average soil moisture conditions instead of direct measurements. The riparian zones were mapped by walking along the outer edges of the vegetation communities indicating wet conditions while continuously logging GPS coordinates. This resulted in polygons encompassing wet riparian zones on both sides of the streams (Figure 8).

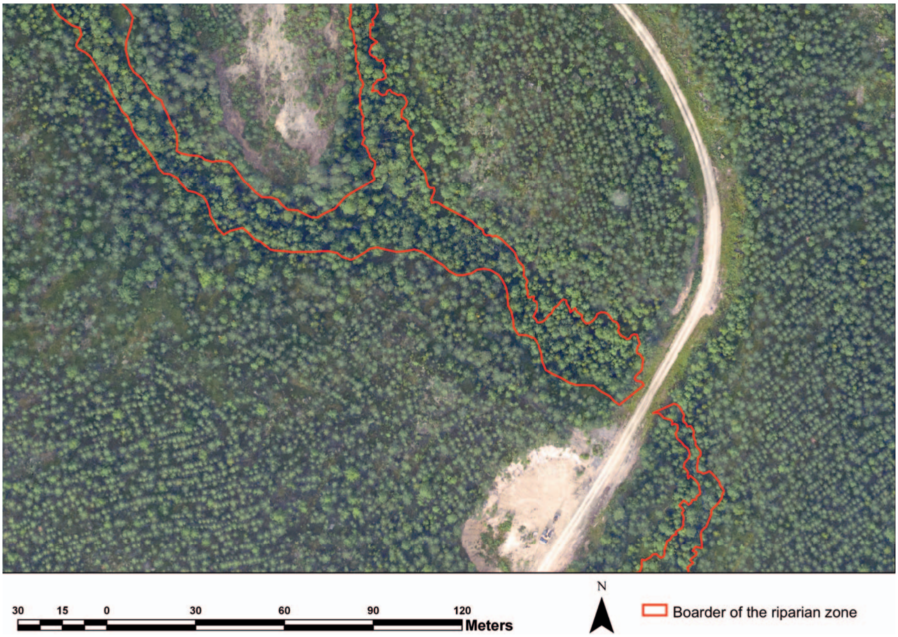

Figure 8: Example of a wet riparian zone (indicated by the red lines) mapped in Study IV.

3.3 Topographical modelling

3.3.1 DEM Pre-processing

In all of the studies, we used the Swedish National elevation model generated by the Swedish Mapping, Cadastral and Land Registration Authority using LiDAR (Figure 5a). This DEM has a cell resolution of 2 m and was generated from a point cloud with a point-density of 0.5-1 points m^{-2} and horizontal and vertical errors of 0.4 m and 0.1 m, respectively. This DEM includes small-scale anthropogenic features such as railroads, road banks and bridges. Therefore, it had to be pre-processed before use in hydrological modelling. In Study I, several methods for pre-processing the DEM and three DEM resolutions (4, 8 and 16 m) were evaluated. The evaluated pre-processing methods can be classed in three categories: algorithms that fill sinks, algorithms that breach sinks and algorithms that utilize a combination of both filling and breaching to remove sinks. There is also an option to burn known stream networks into DEMs. However, forest hydrology is often poorly mapped and only streams distinguishable from aerial photos are displayed on current maps which makes stream burning questionable (Lindsay and Dhun 2015). Nevertheless, some information can be used from legacy stream networks. Notably, it seems reasonable to assume that locations of stream-road crossings would be easier to distinguish from aerial photos because openings in the canopy along roads facilitate their identification. Therefore, streams from existing maps were burned into the DEM where they crossed a road, but only for a short distance (≤ 50 m), corresponding to the maximum distance required to burn across the largest road embankments in the catchments.

The results from Study I were used to pre-process the Swedish DEM for use in Studies II, III and IV as well as the Canadian DEM for use in Study IV. The results from Study I suggested a three-step breaching approach, as described below:

I) Stream lines from the 1:12 500 scale property map produced by the Swedish Mapping, Cadastral and Land Registration Authority were burned 1 m into the DEM of agricultural land using the 'burn streams' tool in Whitebox GAT 3.4 (Lindsay 2014; Lindsay 2016).

II) Stream lines from the property map were burned across road lines from the property map using the 'burn streams at roads' tool in Whitebox GAT 3.4, as described in Article I.

III) Remaining sinks were resolved by the complete breaching algorithm developed by Lindsay (2015) using Whitebox tools (Lindsay 2018).

3.3.2 Stream extraction

In all of the studies, we used streams extracted from a DEM, as illustrated in Figure 3. A flow pointer grid and flow accumulation grid were extracted from the hydrologically correct DEM using Deterministic-8 (D8) (O'Callaghan and Mark 1984). D8 was used as it is computationally effective and gives results that differ little from those of more complex flow routing algorithms on high resolution DEMs (Leach et al. 2017). Streams were then extracted from the flow accumulation grid using stream initiation thresholds of 0.5, 1, 2, 5, 10, 15 and 30 ha. The 2 ha stream network was used in Study I, while all seven of these thresholds were used in Studies II and III. In Study IV, slightly different thresholds (0.5, 1, 2, 4, 8, and 16 ha) were used, for no particular reason.

3.3.3 Elevation Above Stream and Depth To Water

In Study III, several terrain indices for mapping wet soils were evaluated, and terrain indices specifically for mapping riparian zones were evaluated in Study IV. In both of these studies, EAS and DTW indices were used.

EAS values were calculated using the source layer containing the extracted streams described above, the D8 pointer grid used to extract streams, and the original DEM. The values were calculated as the difference in elevation between a grid cell in the landscape and the nearest source cell representing surface water, measured along the downslope flow path determined by the D8 pointer grid (Rennó et al. 2008; Jencso et al. 2009; Nobre et al. 2011). This was done for each of the stream networks described above.

DTW is similar to EAS, since they are both based on the difference in elevation between a source grid and surrounding landscape, but DTW is calculated along the least-cost-path rather than downslope flow path determined by a D8 grid. The cost is the slope of the DEM calculated by equation (1), as described by Murphy et al. (2007) and Murphy et al. (2008a).

$$\text{DTW (m)} = [\sum \frac{dz_i}{dx_i} a] xc \qquad \text{(Equation 1)}$$

Here, *dz/dx* is the slope of a cell along the least-elevation path, *i* is a cell along the path, a equals 1 when the path crosses the cell parallel to cell boundaries and √2 when it crosses diagonally; *xc* is the grid cell size (m).

3.3.4 Topographic Wetness Index

The TWI describes how likely an area is to be wet, based on its specific catchment area and local slope as described in equation (2), where As is the specific catchment area and slope is the slope of the grid cells in degrees (Beven and Kirkby 1979; Moore et al. 1991).

$$\text{TWI} = \ln\left(\frac{As}{tan(slope)}\right) \qquad \text{(Equation 2)}$$

In our studies it was calculated using the D-infinity flow routing algorithm (Tarboton 1997) and wetness index tool in Whitebox GAT 3.4. Since TWI is scale-dependent, we resampled the 2 m DEM to generate 24 m and 48 m DEMs for Article III as these have been found to be acceptable resolutions for TWI in the Krycklan catchment in northern Sweden (Ågren et al. 2014).

3.3.5 Other factors affecting hydrological modelling

Local topography is recognized as an important factor for controlling soil moisture (Moeslund et al. 2013) and one way to extract values of local topography is to use the standard deviation of elevation from a DEM. We used moving windows with 5x5, 10x10, 20x20, 40x40 and 80x80 grid cells from a 2 m DEM to calculate standard deviations of elevation at each field plot. High values indicate steep terrain while low values indicate flat terrain.

Quaternary deposit is also an important factor for soil moisture in Sweden, since they strongly influence the permeability and drainage capacity of soils. Therefore, distributions of these deposits were extracted from maps created by the Swedish Geological Survey. Open wetlands are more accurately mapped on the 1:12 500 scale property map, so these were used in addition to the peat layer from the quaternary deposits map. There was considerable variability in runoff between different regions in Sweden and across seasons (Figure 5). High runoff should reflect high groundwater levels, which in turn could affect the distribution of wet soils. Thus, S-HYPE (Arheimer et al. 2011) was used to model seasonal and annual runoff in 33 605 sub-catchments between 1982 and 2015.

3.3.6 Maps currently used in management

As field-mapping wet and moist soils is very time-consuming, it cannot be used to regional or national scale maps. In studies III and IV we compared maps from different sources available for forest companies in Sweden and Canada today. First we evaluated the performance of currently used topographical maps. We used wetlands from topographical maps in Study III and fixed-width buffers from streams derived from topographical maps in Study IV. Buffers of 5, 10, 20, 30 and 40 m were applied to stream lines from topographical maps in both Sweden and Canada.

In both Sweden and Canada, DTW maps are currently used by some companies in forest management. The Swedish Forest Agency (SFA) introduced a DTW map in 2015 that was accessible to private Swedish forest owners. The DTW map used by the SFA was calculated by setting two thresholds: a stream initiation threshold set to 1 ha, and a height above stream threshold set to ≤1 m. A similar DTW map was available in New Brunswick, Canada, and was used by the large forest company Irwing in Black Brook. This DTW map had a stream initiation threshold of 4 ha and height above stream threshold of <1 m. From a management perspective, it is interesting to evaluate how well these national and regional DTW maps capture ‘wet’ areas (Article III) and riparian zones (Article IV). The Swedish DTW map was evaluated against the NFI plots in Article III and riparian zones in the Swedish catchments (Norralaån and Krycklan) in Article IV. The Canadian map was evaluated using data from the Canadian catchment (Black Brook) in article IV.

3.4 Data analysis

3.4.1 Statistical evaluations

Most results presented in this thesis and appended papers concern the presence or absence of stream channels, or classification of wet and dry soils. Therefore, confusion matrixes were used to evaluate classifications described in Articles II, III and IV. A confusion matrix tabulates true positives (TPs, accurate predictions of a feature on a map), false positives (FPs, inaccurate predictions of a feature), true negatives (TNs, accurate predictions of the absence of a feature), and false negatives (FNs, misses of an existing feature). For this purpose, we used Mathews Correlation Coefficient (MCC) (Boughorbel 2017) in Study II, and Cohen's kappa index of agreement in Studies III and IV. Residuals from the confusion matrix from the optimal stream channel network obtained in Study II were converted into an ordinal variable, 1 for FN and 2 for FP, then analyszed by Orthogonal Projections to Latent Structures Discriminant Analysis (OPLS-DA) using SIMCA 14.

3.4.2 Machine Learning

The results from Study II revealed high potential to improve channel networks by taking spatial variability of factors such as quaternary deposits and climatic parameters into account. This was done in Study III by using machine learning (ML). ML is a datamining technique that finds patterns in datasets and uses them to predict new data (Kotsiantis 2007). Several ML algorithms are available (Hastie et al., 2009), but the optimal algorithm depends on the nature of the problem and it is usually recommended to explore the utility of several algorithms (Maxwell et al. 2018; McBratney et al. 2003). Therefore, we tested four types of commonly used ML algorithms in Study III: artificial neural network (ANN) (Ripley 2014), random forest (RF) (Breiman 2001), support vector machine (SVM) (Chang at al 2008) and naïve Bayes classification (NB) (Bhargavi and Jyothi 2009). The R package Caret (Kuhn et al. 2012) was used to implement all machine learners. Multicollinearity among the variables was tested and variables with a correlation over 0.9 were excluded prior to analysis. The NFI dataset was split, then 75 % was used for training and 25 % for tests, and all ML algorithms were parameterized and tuned using a grid-search approach in combination with 10-fold cross-validation to find the best fitting model. The best tuned models were applied to the NFI test dataset in Study III and evaluated using Cohen's kappa index of agreement. The field-mapped riparian zones from Krycklan and Norralaån were used as test data in Study IV.

3.4.3 Working with big data

This chapter ends with a few words regarding the challenges of working with high resolution data over large areas. Most researchers who have worked with GIS have experience of long processing times, random errors and frustrating crashes, due both to slow computers and poorly optimized software. For small study areas, the problems can be acceptable and handled with patience. However, when the study site consists of an entire nation, even a small one like Sweden, they become more challenging. For example, the size of the Swedish DEM is 1.2 TB when stored in a 32 bit float format (Whitebox's native raster format). When this data is being processed the computer must be able to hold one or several copies in the computer's random access memory (RAM), which is usually 8 to 16 GB in an average current laptop. The solution was to split the DEM into 2 818 sub-catchments, each having a 2 km overlap with surrounding catchments to reduce edge effects during stream extraction. These sub-catchments were processed separately with the added bonus that the whole processes could be parallelized. Modern computer processors have several cores and parallelization means that each one of these cores can work on separate sub-catchments simultaneously, thereby significantly reducing processing time. This scales well until the system RAM is full. The decision to split Sweden into exactly 2 818 sub-catchments was based on the size of sub-catchments we could fit in the system RAM. Further, all GIS tools from various GIS software then had to be adapted to run in parallel using efficient programming and scripts. As a result it was possible to use relatively cheap consumer hardware (3 000 EUR) to build a workstation capable of, for example, breaching the 1.2 TB DEM in less than 12 hours, making this a cost-effective approach. Parallelization also opens up the possibility to utilize high performance clusters, i.e. 'super computers'. However, this is not always a practical approach during development since trial-and-error is a natural part of the workflow.

The next hurdle to overcome was storage of the sheer amount of data produced. Each of the 30 layers used in Studies II and III resulted in an additional 1.2 TB of data. A possible solution is cloud storage, but that would mean transferring data over the internet, which would take 2-3 days for each calculation. The solution we applied was to build a local network access storage unit (NAS) next to the workstation and bypass the university network.

4 Summary of results and discussion

4.1 Pre-processing and stream networks

Previous studies have shown that current maps are inaccurate and often lack headwater streams altogether (Bishop et al. 2008; Persendt and Gomez 2016). This was supported by findings of Studies I and II, and a remarkable result from Study II is that up to 81.5 % of all stream channels in the NILS database are missing on current maps.

Results from Study I showed that the accuracy of stream networks increased with increasing DEM resolution, at least to 2 m resolution, the highest resolution considered in Article I. This is consistent with previous research, and in theory the highest resolution data should produce the most accurate stream channel networks (Shortridge and Barber 2005). However, higher resolution is not suitable for all hydrological purposes or terrain analysis (Gonga-Saholiariliva et al. 2011). Coarse DEMs perform better for indices such as TWI that are influenced by the size of hillslopes (Creed et al. 2003). Moreover, there is always a trade-off between DEM resolution and processing time, since the number of data points to process increases dramatically with increasing resolution, but higher resolution DEMs contain more detailed information about small-scale features, such as forest ditches (Hasselquist et al. 2017). The increased processing time is somewhat mitigated by efficient algorithms and exponentially increasing processing power of computers.

Another interesting finding was that stream networks extracted from DEMs that had been breached rather than filled created more accurate stream networks, regardless of DEM resolution. A major advantage of breaching is that it conserves more of the original flow path information up-stream of breached roads (Figure 9).

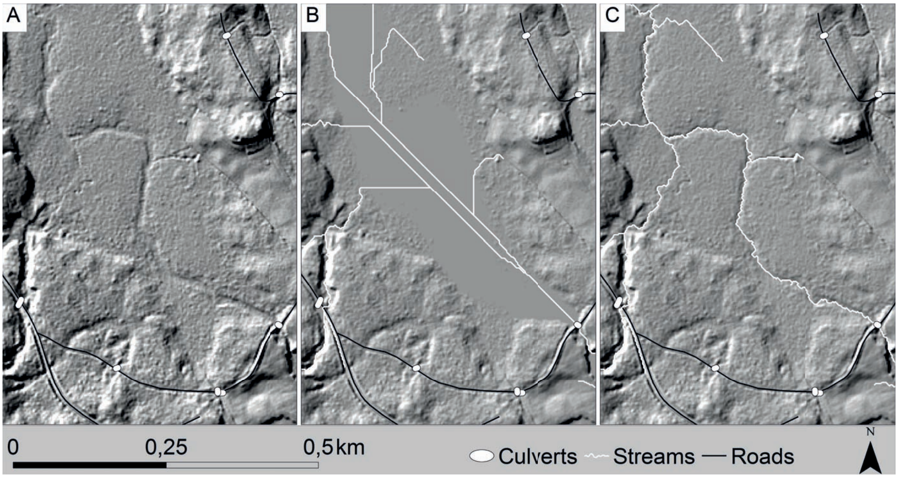

Figure 9. One of the most important differences between filling and breaching is in their effects on upstream flow paths. A) A stream channel is visible in the original 2 m DEM. B) Filling creates a flat area of arbitrary values upstream of the road embankment, resulting in parallel and unrealistic stream segments. c) Breaching utilizes flow path information in the area upstream of the road embankment. From Article I. DEM © Lantmäteriet.

Building on Article I, breaching was used to extract stream networks from the Swedish 2 m DEM. These new stream networks were more accurate than currently available stream networks, and the most accurate stream network was 4.5 times longer than the network extracted from the Swedish property map. This is quite alarming since low order streams are suggested to be disproportionately high CO_2 emitters, accounting for more than 70 % of total emissions from streams and rivers (Raymond et al. 2013). Wallin et al. (2018) calculated the evasion from a 400,000 km stream network based on a 50 m DEM and estimated that total losses of CO_2 and CH_4 amounted to 2.7 and 0.02 Tg C yr-1, respectively. Our most accurate stream network was 6.6 times longer than the network used by Wallin et al. (2018). This indicates that the CO_2 and CH_4 evasion in Sweden, during most of the year (except in extremely dry periods), is even larger than the estimates presented by Wallin et al. (2018) suggest. It also demonstrates the importance of an accurate stream network for upscaling estimates generated in aquatic and climate research, and constraining the C budget.

The most accurate network presented in Article II was based on a fixed 2 ha stream channel initiation threshold. We used a fixed threshold for channel initiation, but there are other methods to determine positions of channel heads based on finding the threshold where water has enough energy to start eroding the soil and forming a channel head. One is the slope-area method, which has been used to derive slope-area threshold relationships from DEMs (Avcioglu et al. 2017; Imaizumi et al. 2010). Such methods provide better indications of channel heads in steep terrain than in flatter terrain (McNamara et al. 2006). However, the algorithms are designed to detect naturally formed channel heads. Thus, they may provide inaccurate results in many parts of Sweden and other heavily drained countries, such as Finland and the Baltic States (Lõhmus et al. 2015), where there are strong anthropogenic influences and numerous man-made channels draining the landscape.

Of the streams included in the NILS database, 63 % are ditches, mostly on forested land. These ditches are generally small (<2 m) and it seems reasonable to assume that a DEM with 2 m resolution still misses important information about these ditches (Hasselquist et al. 2017). Forest ditches have been dug for various purposes, for example, to increase rational agricultural production (Avilés et al. 2018), to increase timber production on wet forest soils or mires (Lõhmus et al. 2015), and to stabilize roads (Kalantari and Folkeson 2013). This practice has fundamentally changed the hydrology of the landscape, where many patches of wet soils with subsurface flow have been ditched, draining the land, lowering the water table and creating many more channels in the landscape. There are also substantial spatial variations that impact the expansiveness of stream networks. Variations in runoff, quaternary deposits and topography among sites can affect the channelization of water, and an analysis of the residuals showed that there is still room for improvement by taking these spatial patterns into account.

Despite these difficulties, the results presented in Articles I and II demonstrate that topographical modelling of streams extracted from a DEM can provide better results than current maps. Not only does it capture more headwater streams, but the channels also follow the inundated channels in the DEM (Figure 9c) (Murphy et al. 2008b). Thus, it places the streams more correctly than current maps, which merely have lines drawn in streams' approximate positions. These new derived stream channel networks also form an integrated drainage network. During road construction this can be used to correctly place and dimension road culverts, which can reduce problems of roads washing out during flood events (Prasad et al. 2005).

The NILS database did not contain consistent information about flow conditions in stream channels, and previous research on temporal dynamics in stream networks in northern Sweden indicates that streams in most of these channels are ephemeral and the length of active streams varies greatly (Ågren et al. 2015). If accurate GPS positions of stream heads were available it would be possible to expand the analysis with multiple logistic regressions, as suggested by Russell et al. (2015). In addition, if information regarding stream flow was collected it would be possible to use more advanced models, such as the

PRObability of Streamflow PERmanence (PROSPER) model developed by the U.S Geological Survey (Jaeger et al. 2019) or even ML to predict the probability of each stream channel containing water. Equipping the NILS surveyors with accurate GPS units and updated instructions would open up new possibilities for accurately modelling headwater streams in Sweden.

4.2 Wet area mapping

Attempts to map missing surface water continued in Studies III and IV, but with a focus on wet areas such as peatlands and wet soils near streams and lakes. Previous studies had shown that current maps of wet areas lack accuracy and suggested that topographical modelling from a DEM could potentially generate better maps (Murphy et al. 2008a). Initial comparisons of field plots from the NFI and the Swedish property map showed that current maps only correctly classified 36 % of all field plots located on ‘wet’ soils. Since the property map mostly includes open peatlands that are visible from aerial photography, it seems reasonable to assume that the remaining 64 % are located on drained and forested mires or in the riparian zone near streams and lakes. In 2015, the SFA introduced a DTW map that is accessible online to private Swedish forest owners. The SFA’s DTW map provided substantially better predictions than the property map (kappa values: 0.55 and 0.39, respectively) and correctly classified 73 % of all ‘wet’ field plots. However, it also classified 17 % of all ‘dry’ field plots as ‘wet’. Results presented in Article III showed that machine learning can be used to further improve the accuracy of maps of wet areas by taking climate, topography and distributions of quaternary deposits into account. Random forest (RF) and artificial neural networks (ANN) performed best, yielding kappa values of 0.65, correctly classifying 75 % of all ‘wet’ plots and only classifying 10 % of the ‘dry’ plots as wet. The machine learning-generated wet area map (MLWAM) model presented in Article III identified 75 % of the ‘wet’ areas, much more than the 36 % identified from the topographical map (Figure 10).

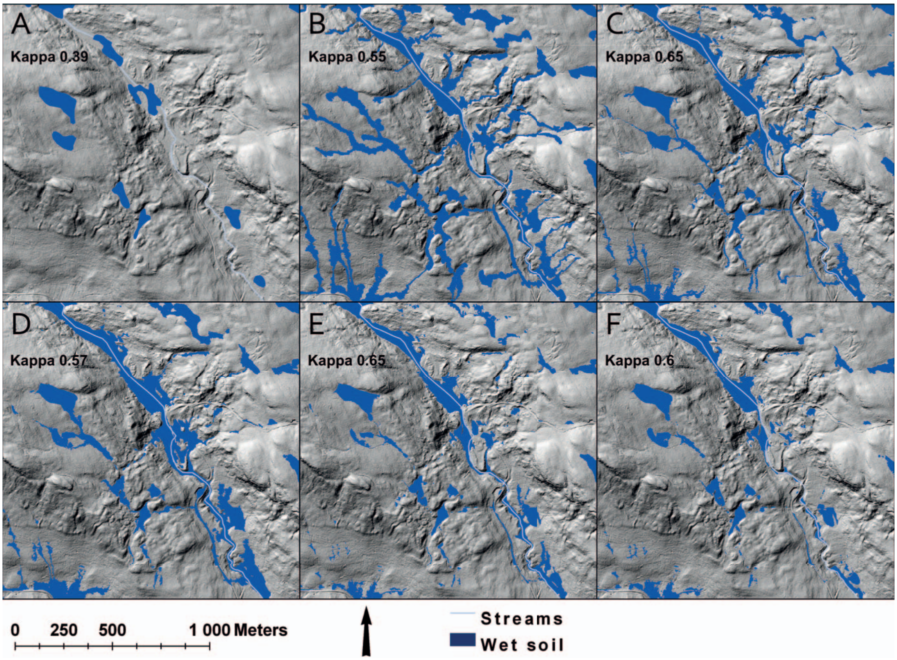

Figure 10. Wet areas superimposed on a hillshade of a DEM in the Krycklan catchment. A) The wetlands from the property map, which misses many of the wet areas. B) Swedish Forest Agency DTW map, which tends to overestimate areas' wetness. Panels C-F show areas in the 'wet' class identified using four machine learners: C) Random Forest, D) Naïve Bayes, E) Artificial Neural Network, and F) Support Vector Machine. Even the worst of these (naïve Bayes) generated a better map than the SFA DTW map, but the Random Forest and Artificial Neural Network algorithms generated the best results. The kappa values in the panels indicate the maps' performance for the entire forest landscape of Sweden, although the panels show a very small sub-section of the Krycklan catchment. From Article III. DEM © Lantmäteriet.

Several machine learners can map probabilities of their predicted classifications' accuracy (Figure 11), and the resulting probability maps can be used to plan off-road driving of heavy forestry machines to avoid deep rutting. While soil moisture is not the only variable affecting soil bearing capacity (Pohjankukka et al. 2016; Mohtashami et al. 2017), they can still be used to identify sensitive areas near streams where ruts would cause exports of sediments to streams due to the high connectivity to surface waters. The use of logging residues can also be optimized and planned in advance to reduce negative impact on nearby surface water. Logging residues can be used to build slash mats in 'wet' areas to reduce rutting from heavy machines and harvested in 'dry' areas for bioenergy production (Figure 11). This would help balance green energy production and surface water protection goals.

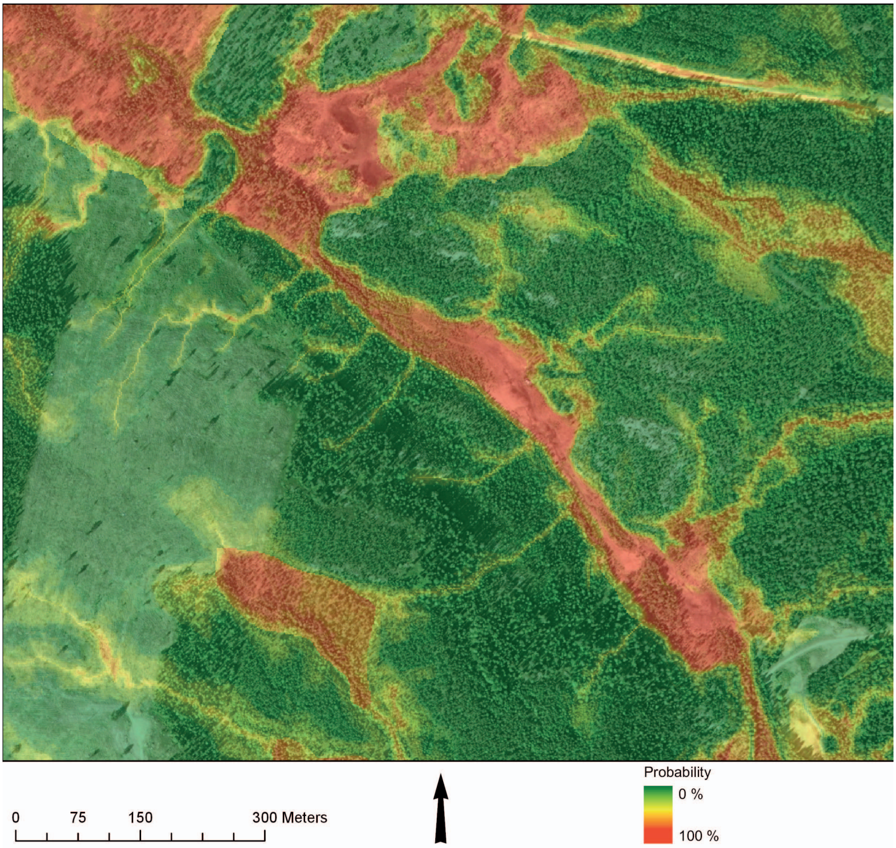

Figure 11. Illustrative map of probabilities (%) of 'wet' areas predicted by one of the most accurate machine learners (Random Forest). Areas with high, intermediate and low probabilities of being classified as 'wet' are red, yellow and green, respectively. Ortophoto © Lantmäteriet.

Aerial photographs have often been manually interpreted and show small-scale features, while coarse resolution data from satellite images have been most widely used for large-scale studies. Further development has focused on combining data from several different sources, such as digital terrain models and multispectral satellite images (Maxwell et al. 2016; Guo et al. 2017). LiDAR has enabled mapping of small-scale features beneath dense canopy cover (Murphy et al. 2008a; Richardson et al. 2010), but LiDAR data have been scarce and often limited to small study areas. The most recent advances have involved combinations of LiDAR and multispectral imagery. Rapinel et al. (2015) combined canopy height models, micro topography and intensity return from LiDAR with multispectral imagery to map wetlands. In Study III, this approach was extended by combining high-resolution wet area indices derived from LiDAR with data from other sources such as legacy maps of quaternary deposits, wetlands and climate data. The result is a model that creates a high resolution (2 m) map with an overall accuracy (for classifying 'wet' areas) of 84 %.

4.3 Mapping the riparian zone

Mapping wet soils within the riparian zone was one of the main objectives of the research underlying this thesis, and Study IV focused on evaluating the accuracy of topographically delineated riparian zones and comparing them to fixed width buffers from topographical maps currently used. Fixed-width buffers around streamlines from topographical maps only had slight to fair agreement in the two Swedish catchments, but had better (fair to moderate) agreement in Black Brook. This highlights the importance of a new approach to aid practitioners in planning riparian protection zones around these small streams. These headwaters make out the majority of any given stream network and are the capillaries of the stream networks and the associated riparian soils yet they are known as *Aqua Incognita.* Previous studies that have attempted to map riparian zones have either used course resolution data (Baker et al. 2006) or focused on riparian zones around large streams or rivers (Johansen et al. 2010; Jeong et al. 2016). However article IV focused on mapping riparian zones around headwater streams using high resolution DEMs (2 m).

Both the SFA DTW map with national coverage of Sweden and the NB DTW map provided more accurate indications of riparian zones than fixed width buffers from corresponding topographical maps. Further, Study IV demonstrated that maps of stream networks extracted from both DTW and EAS maps were highly sensitive to the thresholds used for calculations. Article IV clearly showed that the models needed to be adjusted for local conditions. Even within the relatively small Krycklan catchment the optimal stream initiation thresholds for DTW varied due to spatial differences in quaternary deposits (Ågren et al. 2014). This variability highlights the need for more research in order to properly capture the small scale hydrological features of the riparian zones around headwater streams.

A possible way of handling variability in topography and soils is to use ML to adjust maps of wet areas in accordance with local conditions. The MLWAM model suggested in Article III was trained to map wet areas in general, rather than solely riparian zones. However, a slightly modified version of MLWAM, which also included a soil depth model from the Swedish geological survey, was evaluated against the field mapped riparian zones in Study IV. This slightly modified version of the MLWAM model provided the most accurate map of riparian zones in Krycklan (Kappa 0.54) and a more accurate map than the SFA DTW map of Norrarlaån (Kappa 0.4). So, despite not being specifically trained on riparian zones, the MLWAM methodology seems a possible approach for mapping riparian soils across larger regions. ML has been used to map riparian zones before, and Chignell et al. (2018) recently used an integrative modelling approach to model riparian zones in the Cache la Poudre River watershed, Colorado, USA with rather impressive under-the-curve values of 0.98. However as mentioned above, most studies use course resolution data such as satellite imagery and often focuses on larger water courses as rivers (Baker et al. 2006). Article IV focused on mapping relatively narrow riparian zones around headwater streams but it seems reasonable to assume that modified MLWAM maps would also capture riparian zones around large streams and rivers. This possibility was not evaluated as the field data were from headwater systems.

4.4 Management implications

It is well established that headwater streams and wet areas play important ecological and biogeochemical roles in the boreal zone (Creed et al., 2011). Research on effects of forestry operations near these areas has resulted in new management policies, but effective tools to implement these policies in practice have not yet been developed, and current maps of streams and wet areas lack accuracy (Murphy et al. 2008; Benstead and Leigh 2012). However, the number of national LiDAR campaigns is growing (Figure 12) and all the data processing required to map wet areas can be done with open source software and consumer-grade hardware within reasonable amounts of time. Methods described in this thesis are therefore relatively cost-effective ways to map streams and wet areas so they can be considered in practical forestry planning.

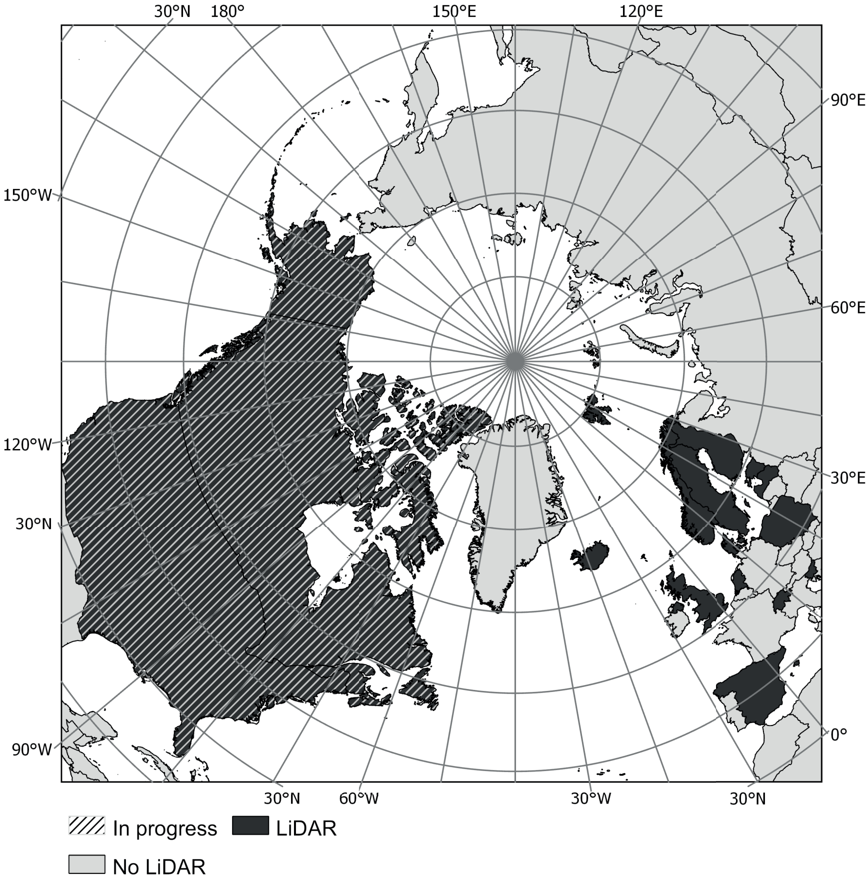

Figure 12: Countries in the northern hemisphere with complete or ongoing national LiDAR campaigns.

In practical applications, these maps should be used during the planning of harvesting. This can be done in three steps. First, they can be used to identify the wettest harvesting stands and schedule them for harvesting during frozen periods and prioritizing drier sites for spring or fall. Secondly, once a stand has been selected these maps can be used to design hydrologically adapted protection zones around lakes and streams. In practice, this means harvesting all the way to the water's edge in drier sections of riparian zones, where the risk of rutting is relatively small, and leaving a wider protection zone around DRIPS (Ploum et al 2018) and wet sections of the zones (Kuglerová et al. 2017) (Figure 13). This would serve to both emulate natural disturbances (Kreutzweiser et al. 2012) and reduce environmental impacts in hydrologically active and sensitive areas. Leaving a wider buffer in wet areas might seem like a costly practice, but Tiwari et al. (2016) showed that forest productivity tends to be lower, and fewer commercially valuable tree species tend to be present, in wetter areas. Financial losses are further offset if trees are cut closer to the stream edge in drier sections along the stream. However, it is also important to consider effects of, for example, shading and leaf litter when designing protection zones. The third planning step in which these maps can be used is planning off-road driving. Extraction roads, in particular, should be carefully planned since they are expected to carry the heaviest traffic (in loads) (Mohtashami et al. 2017). Logging residues can be used to reinforce extraction roads, but due to increasing demand to use logging residues for bioenergy this only done where necessary for trafficability (Eliasson and Wästerlund 2007). Maps like the one in figure 11 could be used to plan extraction roads in advance to optimize the use of logging residues. However, it is important to remember that ca. 85 % accuracy in mapping wet areas implies that ca. 15 % of wet areas are incorrectly mapped. So, when used in practise it is important to field-validate the suggested stream crossings, riparian zones, DRIPS etc. However, we argue that use of the maps will speed up this process, as it is not necessary to ground truth entire stands, and more attention can be paid to key areas.

Figure 13. Illustration of how wet areas maps can be used in practical operations. Trees can be harvested closer to the water's edge in drier sections of riparian zones, where the risk of rutting is relatively small, and leaving a wider protection zone around wet areas and DRIPs. (Image Fredrik Saarkoppel).

There is also significant temporal variability in distributions of wet soils that is not taken into account in these maps. On one hand soils tend to be frozen during winter, at least in northern regions of the boreal zone, which greatly increases trafficability. On the other hand, snowmelt and rain events cause almost all soils to become wet or moist, which increases their susceptibility to rut formation (Mohtashami et al. 2017). Thus, ruts also often occur in areas that are normally dry. However, forestry operations in dry areas on the map (Figure 11) pose smaller risks of increased sediment transport and nutrient/mercury leaching than operations in the wet areas where the connectivity to surface waters is higher (Ågren et al. 2015). Other aspects of forestry can be optimized within sites with the help of accurate maps of wet soils. For example, seedling selection can be optimized with respect to soil moisture and water availability (Murphy et al. 2009), and soil scarification can be avoided in sensitive areas.

5 Conclusions

The overall conclusions of this thesis are that high-resolution DEMs derived from airborne LiDAR can be used to create maps of previously unmapped streams and wet areas. These maps can be used to assist the design of hydrologically adaptive protective zones near streams and plan off-road driving with heavy forestry machines to reduce rutting in sensitive areas close to streams. Specific conclusions and recommendations drawn from each study are summarized below.

I The accuracy of stream networks, in terms of correct culvert intersections, increased with increasing DEM resolution. Breaching rather than filling improved the accuracy of stream networks extracted from DEMs at all resolutions, and had less impact in terms of changes in area and absolute volume. The difference in accuracy between breaching and filling increased with increasing resolution. The accuracy also increased when streams from the topographic map were burned across roads from the topographical map, for all methods and resolutions.

II Most stream channels narrower than 6 m were missing on the Swedish property map. A more accurate stream network map has many uses in landscape planning and best management practice. Also, incorrect representations of stream networks severely affect upscaling of the results of aquatic and climatic research, a problem that increases with scale. This study shows that a solution to this problem could be to map stream channel networks from high-resolution DEMs. For the study region of Sweden, which was used as a test bench, a 2 ha flow initiation threshold yielded the optimum stream network, increasing MCC from 0.39 on the property map to 0.46. However, when applying the same methodology to other biomes it is necessary to adapt the models and find the optimum flow initiation threshold for each landscape.

III Machine learning can be used to create new and more accurate high-resolution maps of wet soils. These maps are better than previously used fixed-threshold DTW maps. The new maps can, for example, be used to suggest machine-free zones near streams and lakes to prevent rutting from forestry machines, thereby reducing sediment, mercury and nutrient loads to downstream streams, lakes and the Baltic Sea.

IV The SFA/NB DTW maps and MLWAM maps do provide a clear improvement compared to the topographical maps. Additionally our study show that there is still a need for further improvements of the mapping of small scale variability of the riparian zones around headwaters. LiDAR is still scarce in most of the boreal zone but there is a steady increase of national Li-DAR campaigns. LiDAR based high resolution DEMs are becoming accessible in many countries so digital mapping of riparian zones could be a cost effective way to optimize management of riparian zones around headwater streams. Countries with intensive forestry often have extensive national forest inventories that could be used to train a machine learner to further increase the accuracy of digital mapped riparian zones.

6 Future research directions

The variables included in the residual analysis in Study II only explained 15 % of the variability in the over- and under-estimation of stream networks. However, we did not investigate the effects of DEM quality. Any methods that use DEMs to derive hydrological indices are limited by the quality of the original DEM and the information it contains. Just like aerial photography is limited by visibility through the canopy cover, LiDAR is limited by the amounts of light pulses that get back to the sensor. Fewer returns limit the resolution of DEMs derived from them and small-scale features such as forestry ditches will be lost. Extensive ditch networks in landscapes can cause errors in flow directions since some ditches are too small to be properly represented in some DEMs. Thus, one research priority is to improve the quality of LiDAR DEMs in order to retain features specifically for hydrological modelling. Line detection algorithms that can be used to map small forest ditches could improve stream network accuracy further and different algorithms to create DEMs from point clouds should also be evaluated. Citizen science could be an effective resource for generating field data on stream heads throughout a country in order to properly evaluate how to incorporate the landscape and climatic variability in the models. Modern phones have decent GPS units that could be used to collect moderately accurate locations of stream heads and dates of observation.

In Article III and to some extent Article IV we showed that machine learning can be used to map wet areas and riparian zones. Perhaps a machine learner trained exclusively on NFI plots near the riparian zone would predict riparian zones more accurately than the MLWAM suggested in Article III. The classical machine learning methods evaluated in Study III predicted wet areas that substantially agreed with areas classified as wet from field observations However, the most recent advances in machine learning have been in the domain of deep learning (Lecun et al. 2015). I recommend that future studies also evaluate the performance of deep convolutional networks for wet areas mapping. However, effective ML generally, and deep learning particularly, requires large amounts of training data, which can be difficult to acquire in fields like ecology and soil science since collecting field data is labour-intensive and expensive. Therefore, it is important to investigate different sources of field data and evaluate their quality, particularly the accuracy of their GPS coordinates. Continuation of national inventories of landscapes and forests is also important, to provide high quality training data, not only for mapping wet areas but also for digital soil mapping generally and future ecological innovations.

Finally, I recommend increases in interdisciplinary efforts involving collaborations between data scientists, soil scientists, hydrologists and ecologists. Recent developments in ML enable inclusion of data from more sources, even if their individual quality might be poor. For example, LiDAR signal intensity can be combined with satellite images without researchers having to specify the relationship between them. ML can detect patterns within datasets and use them to predict wet areas or riparian zones, or perhaps even soil types. LiDAR provides vast amounts of information, but efficiently processing the data requires knowledge of both efficient programming and an understanding of how the results should be used.

References

Ågren, A. M., W. Lidberg, M. Strömgren, J. Ogilvie, and P.A. Arp. 2014. Evaluating digital terrain indices for soil wetness mapping - a Swedish case study. *Hydrology and Earth System Sciences* 18: 3623–3634. doi:10.5194/hess-18-3623-2014.

Ågren, A. M., W. Lidberg, E. Ring. 2015. Mapping Temporal Dynamics in a Forest Stream Network—Implications for Riparian Forest Management. *Forests* 6: 2982–3001. doi:10.3390/f6092982.

Arheimer, B., J. Dahné, G. Lindström, L. Marklund, and J. Strömqvist. 2011. Multi-variable evaluation of an integrated model system covering Sweden (S-HYPE). *IAHS Publication* 345: 145–150.

Ansen, H. 2004. Marktäckedata 2000.

Avcioglu, B., C. J. Anderson, and L. Kalin. 2017. Evaluating the Slope-Area Method to Accurately Identify Stream Channel Heads in Three Physiographic Regions. *Journal of the American Water Resources Association* 53: 562–575. doi:10.1111/1752-1688.12512.

Avilés, D., I. Wesström, and A. Joel. 2018. Status assessment of agricultural drainage ditches. *Transactions of the ASABE* 61. doi:10.13031/trans.12307.

Baker, C., R. Lawrence, C. Montagne, and D. Patten. 2006. Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models. *Wetlands*. doi:10.1672/0277-5212(2006)26[465:MWARAU]2.0.CO;2.

Benstead, J. P., and D. S. Leigh. 2012. An expanded role for river networks. *Nature Geoscience*. doi:10.1038/ngeo1593.

Beven, K. J., and M. J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin* 24: 43–69. doi:10.1080/02626667909491834.

Beven, K 1986. Runoff Production and Flood Frequency in Catchments of Order n: An Alternative Approach. In Scale problems in hydrology, 107–131. *Springer,* Dordrecht. doi:https://doi.org/10.1007/978-94-009-4678-1_6.

Bhargavi, P., and S. Jyothi. 2009. Applying Naive Bayes Data Mining Technique for Classification of Agricultural Land Soils. *IJCSNS International Journal of Computer Science and Network Security*.

Bird, S., D. Hogan, and J. Schwab. 2010. Photogrammetric monitoring of small streams under a riparian forest canopy. *Earth Surface Processes and Landforms*. doi:10.1002/esp.2001.

Bishop, K., I. Buffam, M. Erlandsson, J, H. Laudon, J. Seibert, J. Temnerud. 2008. Aqua Incognita: the unknown headwaters. *Hydrological Processes* 22: 1239–1242. doi:10.1002/hyp.7049.

Bishop, K., J. Seibert, L. Nyberg, and A. Rodhe. 2011. Water storage in a till catchment. II: Implications of transmissivity feedback for flow paths and turnover times. *Hydrological Processes*. doi:10.1002/hyp.8355.

Blackburn, M., J. L. J. Ledesma, T. Näsholm, H. Laudon, and R. A. Sponseller. 2017. Evaluating hillslope and riparian contributions to dissolved nitrogen (N) export from a boreal forest catchment. *Journal of Geophysical Research: Biogeosciences* 122: 324–339. doi:10.1002/2016JG003535.

Boughorbel, S., F. Jarray, and M. El-Anbari. 2017. Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. *PLoS One,* 12, https://doi.org/10.1371/journal.pone.0177678.

Breiman, L. 2001. Random forests. *Machine Learning* 45: 5–32. doi:10.1023/A:1010933404324.

Cambi, M., G. Certini, F. Neri, and E. Marchi. 2015. The impact of heavy traffic on forest soils: A review. *Forest Ecology and Management*. doi:10.1016/j.foreco.2014.11.022.

Chang, C., C. Lin, and T. Tieleman. 2008. LIBSVM : A Library for Support Vector Machines. *ACM Transactions on Intelligent Systems and Technology (TIST).* doi:10.1145/1961189.1961199.

Chignell, S. M., M. W. Luizza, S. Skach, N. E. Young, and P. H. Evangelista. 2018. An integrative modeling approach to mapping wetlands and riparian areas in a heterogeneous Rocky Mountain watershed. *Remote Sensing in Ecology and Conservation*. doi:10.1002/rse2.63.

Clarke, A., R. Mac Nally, N. Bond, and P. S. Lake. 2008. Macroinvertebrate diversity in headwater streams: A review. Freshwater Biology. doi:10.1111/j.1365-2427.2008.02041.x.

Creed, I. F., and F. D. Beall. 2009. Distributed topographic indicators for predicting nitrogen export from headwater catchments. *Water Resources Research*. 45. doi:10.1029/2008WR007285.

Creed, I. F., S. E. Sanford, F. D. Beall, L. A. Molot, and P. J. Dillon. 2003. Cryptic wetlands: integrating hidden wetlands in regression models of the export of dissolved organic carbon from forested landscapes. *Hydrological Processes*. 17: 3629–3648. doi:10.1002/hyp.1357.

Creed, I. F., G. Z. Sass, J. M. Buttle, and J. A. Jones. 2011. Hydrological principles for sustainable management of forest ecosystems. *Hydrological Processes*. doi:10.1002/hyp.8056.

Devito, K., I. Creed, T. Gan, C. Mendoza, R. Petrone, U. Silins, and B. Smerdon. 2005. A framework for broad-scale classification of hydrologic response units on the Boreal Plain: Is topography the last thing to consider? *Hydrological Processes*. doi:10.1002/hyp.5881.

Devito, K. J., I. F. Creed, and C. J. D. Fraser. 2005. Controls on runoff from a partially harvested aspen-forested headwater catchment, Boreal Plain, *Canada. Hydrological Processes*. doi:10.1002/hyp.5776.

Eliasson, L., and I. Wästerlund. 2007. Effects of slash reinforcement of strip roads on rutting and soil compaction on a moist fine-grained soil. *Forest Ecology and Management*. doi:10.1016/j.foreco.2007.06.037.

Elmore, A. J., J. P. Julian, S. M. Guinn, and M. C. Fitzpatrick. 2013. Potential Stream Density in Mid-Atlantic U.S. Watersheds. PLoS ONE. doi:10.1371/journal.pone.0074819.

Fransson, J. 2018. SKOGSDATA 2018. Umeå.

Futter, M. N., E. Ring, L. Högbom, S. Entenmann, and K. H. Bishop. 2010. Consequences of nitrate leaching following stem-only harvesting of Swedish forests are dependent on spatial scale. *Environmental Pollution*. doi:10.1016/j.envpol.2010.08.016.

Gonga-Saholiariliva, N., Y. Gunnell, C. Petit, and C. Mering. 2011. Techniques for quantifying the accuracy of gridded elevation models and for mapping uncertainty in digital terrain analysis. Progress in Physical Geography. doi:10.1177/0309133311409086.

Grayson, R., and A. Western. 2001. Terrain and the distribution of soil moisture. *Hydrological Processes.* doi:10.1002/hyp.479.

Güntner, A., J. Seibert, and S. Uhlenbrook. 2004. Modeling spatial patterns of saturated areas: An evaluation of different terrain indices. *Water Resources Research* 40. doi:10.1029/2003WR002864.

Guo, M., J. Li, C. Sheng, J. Xu, and L. Wu. 2017. A review of wetland remote sensing. *Sensors (Switzerland)*. doi:10.3390/s17040777.

Hasselquist, E. M., W. Lidberg, R. A. Sponseller, A. Ågren, and H. Laudon. 2017. Identifying and assessing the potential hydrological function of past artificial forest drainage. *Ambio*. doi:10.1007/s13280-017-0984-9.

Hastie, T., R. Tibshirani, and J. Friedman. 2009. The Elements of Statistical Learning. *Springer* 2001 18: 746. doi:10.1007/b94608.

Hjerdt, K. N., J. J. McDonnell, J. Seibert, and A. Rodhe. 2004. A new topographic index to quantify downslope controls on local drainage. *Water Resources Research* 40. doi:10.1029/2004WR003130.

Imaizumi, F., T. Hattanji, and Y. S. Hayakawa. 2010. Channel initiation by surface and subsurface flows in a steep catchment of the Akaishi Mountains, Japan. *Geomorphology* 115: 32–42. doi:10.1016/j.geomorph.2009.09.026.

Jaeger, K. L., R. Sando, R. R. McShane, J. B. Dunham, D. P. Hockman-Wert, K. E. Kaiser, K. Hafen, J. C. Risley, et al. 2019. Probability of Streamflow Permanence Model (PROSPER): A spatially continuous model of annual streamflow permanence throughout the Pacific Northwest. *Journal of Hydrology X* 2. doi:10.1016/j.hydroa.2018.100005.

Jencso, K. G., B. L. McGlynn, M. N. Gooseff, S. M. Wondzell, K. E. Bencala, and L. A. Marshall. 2009. Hydrologic connectivity between landscapes and streams: Transferring reach- and plot-scale understanding to the catchment scale. *Water Resources Research* 45. doi:10.1029/2008WR007225.

Jensen, C. K., K. J. McGuire, and P. S. Prince. 2017. Headwater stream length dynamics across four physiographic provinces of the Appalachian Highlands. *Hydrological Processes* 31: 3350–3363. doi:10.1002/hyp.11259.

Jenson, S. K., and J. O. Domingue. 1988. Extracting Topographic Structure from Digital Elevation Data for Geographic Information-System Analysis. *Photogrammetric Engineering and Remote Sensing* 54: 1593–1600.

Jeong, S. G., Y. Mo, H. G. Kim, C. H. Park, and D. K. Lee. 2016. Mapping riparian habitat using a combination ofremote-sensing techniques. *International Journal of Remote Sensing*. doi:10.1080/01431161.2016.1142685.

Johansen, K., S. Phinn, and C. Witte. 2010. Mapping of riparian zone attributes using discrete return LiDAR, QuickBird and SPOT-5 imagery: Assessing accuracy and costs. *Remote Sensing of Environment.* doi:10.1016/j.rse.2010.06.004.

Kalantari, Z., and L. Folkeson. 2013. Road Drainage in Sweden: Current Practice and Suggestions for Adaptation to Climate Change. *Journal of Infrastructure Systems* 19: 147–156. doi:10.1061/(ASCE)IS.1943-555X.0000119.

Klaminder, J., R. Bindler, H. Laudon, K. Bishop, O. Emteryd, and I. Renberg. 2006. Flux rates of atmospheric lead pollution within soils of a small catchment in Northern Sweden and their implications for future stream water quality. *Environmental Science and Technology* 40: 4639–4645. doi:10.1021/es0520666.

Kotsiantis, S. B. 2007. Supervised Machine Learning: A Review of Classification Techniques. *Informatica* 31: 249–268. doi:10.1115/1.1559160.

Kreutzweiser, D. P., and S. S. Capell. 2001. Fine sediment deposition in streams after selective forest harvesting without riparian buffers. *Canadian Journal of Forest Research* 31: 2134–2142. doi:10.1139/x02-086.

Kreutzweiser, D. P., P. W. Hazlett, and J. M. Gunn. 2008. Logging impacts on the biogeochemistry of boreal forest soils and nutrient export to aquatic systems: *A review. Environmental Reviews.* doi:10.1139/A08-006.

Kreutzweiser, D. P., P. K. Sibley, J. S. Richardson, and A. M. Gordon. 2012. Introduction and a theoretical basis for using disturbance by forest management activities to sustain aquatic ecosystems. *Freshwater Science*. doi:10.1899/11-114.1.

Kuglerová, L., R. Jansson, A. Ågren, H. Laudon, and B. Malm-Renöfält. 2014a. Groundwater discharge creates hotspots of riparian plant species richness in a boreal forest stream network. *Ecology* 95: 715–725. doi:10.1890/13-0363.1.

Kuglerová, L., A. Ågren, R. Jansson, and H. Laudon. 2014b. Towards optimizing riparian buffer zones: Ecological and biogeochemical implications for forest management. *Forest Ecology and Management* 334: 74–84. doi:http://dx.doi.org/10.1016/j.foreco.2014.08.033.

Kuglerová, L., E. M. Hasselquist, J. S. Richardson, R. A. Sponseller, D. P. Kreutzweiser, and H. Laudon. 2017. Management perspectives on Aqua incognita: Connectivity and cumulative effects of small natural and artificial streams in boreal forests. *Hydrological Processes* 31: 4238–4244. doi:10.1002/hyp.11281.

Kuhn, M., J. Wing, S. Weston, A. Williams, C. Keefer, and A. Engelhardt. 2012. Caret: Classification and Regression Training. https://Cran.R-Project.Org/Package=Caret. doi:10.1126/science.1127647>.

Laudon, H., L. Kuglerova, R. A. Sponseller, M. Futter, A. Nordin, K. Bishop, T. Lundmark, G. Egnell, et al. 2016. The role of biogeochemical hotspots, landscape heterogeneity, and hydrological connectivity for minimizing forestry effects on water quality. *Ambio* 45: 11. doi:10.1007/s13280-015-0751-8.

Leach, J. A. A., W. Lidberg, L. Kuglerová, A. Peralta-Tapia, A. Ågren, and H. Laudon. 2017. Evaluating topography-based predictions of shallow lateral groundwater discharge zones for a boreal lake-stream system. *Water Resources Research* 53: 5420–5437. doi:10.1002/2016WR019804.

Lecun, Y., Y. Bengio, and G. Hinton. 2015. Deep learning. *Nature*. doi:10.1038/nature14539.

van Leeuwen, M., and M. Nieuwenhuis. 2010. Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research*. doi:10.1007/s10342-010-0381-4.

Lidberg, W., M. Nilsson, T. Lundmark, and A. M. Ågren. 2017. Evaluating preprocessing methods of digital elevation models for hydrological modelling. *Hydrological Processes* 31: 4660–4668. doi:10.1002/hyp.11385.

Lidman, F., Å. Boily, H. Laudon, and S. J. Köhler. 2017. From soil water to surface water-how the riparian zone controls element transport from a boreal forest to a stream. *Biogeosciences* 14: 3001–3014. doi:10.5194/bg-14-3001-2017.

Lindsay, J. B. 2014. The Whitebox Geospatial Analysis Tools Project and Open-Access GIS. Conference: GIS Research UK 22nd Annual Conference, At Glasgow, UK: 1–8. doi:10.13140/RG.2.1.1010.8962.

Lindsay, J. B. 2015. Efficient hybrid breaching-filling sink removal methods for flow path enforcement in digital elevation models. *Hydrological Processes* 2: 1. https://doi.org/10.1002/hyp.10648.

Lindsay, J. B. 2016. Whitebox GAT: A case study in geomorphometric analysis. *Computers and Geosciences*. doi:10.1016/j.cageo.2016.07.003.

Lindsay, J. B. 2018. WhiteboxTools User Manual. Guelph. doi:10.13140/RG.2.2.22964.96648.

Lõhmus, A., L. Remm, and R. Rannap. 2015. Just a Ditch in Forest? Reconsidering Draining in the Context of Sustainable Forest Management. *BioScience* 65: 1066–1076. doi:10.1093/biosci/biv136.

Luke, S. H., N. J. Luckai, J. M. Burke, and E. E. Prepas. 2007. Riparian areas in the Canadian boreal forest and linkages with water quality in streams. *Environmental Reviews* 15: 79–97. doi:10.1139/A07-001.

Martz, L. W., and J. Garbrecht. 1998. The treatment of flat areas and depressions in automated drainage analysis of raster digital elevation models. *Hydrological Processes* 12: 843–855. doi:10.1002/(SICI)1099-1085(199805)12:6<843::AID-HYP658>3.0.CO;2-R.

Maxwell, A. E., T. A. Warner, and M. P. Strager. 2016. Predicting Palustrine Wetland Probability Using Random Forest Machine Learning and Digital Elevation Data-Derived Terrain Variables. *Photogrammetric Engineering & Remote Sensing*. doi:10.14358/PERS.82.6.437.

Maxwell, A. E., T. A. Warner, and F. Fang. 2018. Implementation of machine-learning classification in remote sensing: an applied review. *International Journal of Remote Sensing* 39: 2784–2817. doi:10.1080/01431161.2018.1433343.

McBratney, A., M. Mendonça Santos, and B. Minasny. 2003. On digital soil mapping. *Geoderma* 117: 3–52. doi:10.1016/S0016-7061(03)00223-4.

McNamara, J. P., A. D. Ziegler, S. H. Wood, and J. B. Vogler. 2006. Channel head locations with respect to geomorphologic thresholds derived from a digital elevation model: A case study in northern Thailand. *Forest Ecology and Management* 224: 147–156. doi:10.1016/j.foreco.2005.12.014.

Moeslund, J. E., L. Arge, P. K. Bøcher, T. Dalgaard, R. Ejrnæs, M. V. Odgaard, and J. C. Svenning. 2013. Topographically controlled soil moisture drives plant diversity patterns within grasslands. *Biodiversity and Conservation* 22: 2151–2166. doi:10.1007/s10531-013-0442-3.

Mohtashami, S., L. Eliasson, G. Jansson, and J. Sonesson. 2017. Influence of soil type, cartographic depth-to-water, road reinforcement and traffic intensity on rut formation in logging operations: A survey study in Sweden. *Silva Fennica* 51. doi:10.14214/sf.2018.

Moore, I. D., R. B. Grayson, and A. R. Ladson. 1991. Digital terrain modelling: A review of hydrological, geomorphological, and biological applications. *Hydrological Processes* 5: 3–30. doi:10.1002/hyp.3360050103.

Munthe, J., and H. Hultberg. 2004. Mercury and methylmercury in runoff from a forested catchment - Concentrations, fluxes, and their response to manipulations. *Water, Air, & Soil Pollution: Focus* 4: 607–618. doi:10.1023/B:WAFO.0000028381.04393.ed.

Murphy, P., J. Ogilvie, K. Connor, and P. Arp. 2007. Mapping wetlands: A comparison of two different approaches for New Brunswick, Canada. *Wetlands* 27: 846–854. doi:10.1672/0277-5212(2007)27[846:MWACOT]2.0.CO;2.

Murphy, P., J. Ogilvie, C. Mark, Zhang Cheng Fu, R. M. Fan, and Paul Arp. 2008a. Improving forest operations planning through high-resolution flow-channel and wet-areas mapping. *Forestry Chronicle* 84: 568–574. doi:10.5558/tfc84568-4.

Murphy, P., J. Ogilvie, F. Meng, and P. Arp. 2008b. Stream network modelling using lidar and photogrammetric digital elevation models : a comparison and field verification. *Hydrological Processes* 22: 1747–1754. doi:10.1002/hyp.

Murphy, P. N. C., J. Ogilvie, and P. Arp. 2009. Topographic modelling of soil moisture conditions: a comparison and verification of two models. *European Journal of Soil Science* 60: 94–109. doi:10.1111/j.1365-2389.2008.01094.x.

Nobre, A. D., L. A. Cuartas, M. Hodnett, C. D. Rennó, G. Rodrigues, A. Silveira, M. Waterloo, and S. Saleska. 2011. Height Above the Nearest Drainage - a hydrologically relevant new terrain model. *Journal of Hydrology* 404: 13–29. doi:10.1016/j.jhydrol.2011.03.051.

O'Callaghan, J. F., and D. M. Mark. 1984. The Extraction of Drainage Networks from Digital Elevation Data. *Computer Vision Graphics and Image Processing* 28: 323–344. doi:10.1016/S0734-189x(84)80011-0.

Persendt, F. C., and C. Gomez. 2016. Assessment of drainage network extractions in a low-relief area of the Cuvelai Basin (Namibia) from multiple sources: LiDAR, topographic maps, and digital aerial orthophotographs. *Geomorphology*. doi:10.1016/j.geomorph.2015.06.047.

Ploum, S. W., J. A. Leach, L. Kuglerová, and H. Laudon. 2018. Thermal detection of discrete riparian inflow points (DRIPs) during contrasting hydrological events. *Hydrological Processes* 32: 3049–3050. doi:10.1002/hyp.13184.

Pohjankukka, J., H. Riihimäki, P. Nevalainen, T. Pahikkala, J. Ala-Ilomäki, E. Hyvönen, J. Varjo, and J. Heikkonen. 2016. Predictability of boreal forest soil bearing capacity by machine learning. *Journal of Terramechanics* 68: 1–8. doi:10.1016/j.jterra.2016.09.001.

Prasad, A., D. G. Tarboton, C. H. Luce, and T. A. Black. 2005. A GIS Tool to Analyze Forest Road Sediment Production and Stream Impacts. ESRI Users Conference: 1–10.

Rapinel, S., L. Hubert-Moya, and B. Clémentb'. 2015. Combined use of lidar data and multispectral earth observation imagery for wetland habitat mapping. *International Journal of Applied Earth Observation and Geoinformation*. doi:10.1016/j.jag.2014.09.002.

Raymond, P. A., J. Hartmann, R. Lauerwald, S. Sobek, C. McDonald, M. Hoover, D. Butman, R. Striegl, et al. 2013. Global carbon dioxide emissions from inland waters. *Nature* 503: 355–9. doi:10.1038/nature12760.

Rennó, C. D., A. D. Nobre, L. A. Cuartas, J. V. Soares, M. G. Hodnett, J. Tomasella, and M. J. Waterloo. 2008. HAND, a new terrain descriptor using SRTM-DEM: Mapping terra-firme rainforest environments in Amazonia. *Remote Sensing of Environment* 112: 3469–3481. doi:10.1016/j.rse.2008.03.018.

Reutebuch, S. E., R. J. McGaughey, H. E. Andersen, and W. W. Carson. 2003. Accuracy of a high-resolution lidar terrain model under a conifer forest canopy. *Canadian Journal of Remote Sensing* 29: 527–535.

Richardson, J. S., and R. J. Danehy. 2007. A synthesis of the ecology of headwater streams and their riparian zones in temperate forests. *Forest Science*.

Richardson, J. S., R. J. Naiman, and P. A. Bisson. 2012. How did fixed-width buffers become standard practice for protecting freshwaters and their riparian areas from forest harvest practices? *Freshwater Science* 31: 232–238. doi:10.1899/11-031.1.

Richardson, M. C., C. P. J. Mitchell, B. A. Branfireun, and R. K. Kolka. 2010. Analysis of airborne LiDAR surveys to quantify the characteristic morphologies of northern forested wetlands. Journal of Geophysical Research: *Biogeosciences*. doi:10.1029/2009JG000972.

Ring, E., J. Johansson, C. Sandström, B. Bjarnadóttir, L. Finér, Z. Lībiete, E. Lode, I. Stupak, et al. 2017. Mapping policies for surface water protection zones on forest land in the Nordic–Baltic region: Large differences in prescriptiveness and zone width. *Ambio* 46: 878–893. doi:10.1007/s13280-017-0924-8.

Ripley, B. D. 2014. Pattern recognition and neural networks. *Pattern Recognition and Neural Networks.* doi:10.1017/CBO9780511812651.

Rosemond, A. D., J. P. Benstead, P. M. Bumpers, V. Gulis, J. S. Kominoski, D. W. P. Manning, K. Suberkropp, and J. B. Wallace. 2015. Experimental nutrient additions accelerate terrestrial carbon loss from stream ecosystems. *Science*. doi:10.1126/science.aaa1958.

Russell, P. P., S. M. Gale, B. Muñoz, J. R. Dorney, and M. J. Rubino. 2015. A spatially explicit model for mapping headwater streams. *Journal of the American Water Resources Association*. doi:10.1111/jawr.12250.

Seekell, D. A., J.-F. Lapierre, M. L. Pace, C. Gudasz, S. Sobek, and L. J. Tranvik. 2014. Regional-scale variation of dissolved organic carbon concentrations in Swedish lakes. *Limnology and Oceanography* 59: 1612–1620. doi:10.4319/lo.2014.59.5.1612.

Shortridge, C. P. B. & A., and A. S. Christopher P. Barber. 2005. Lidar Elevation Data for Surface Hydrologic Modeling: Resolution and Representation Issues. *Cartography and Geographic Information Science* 32: 401–410. doi:10.1559/152304005775194692.

Sørensen, R., U. Zinko, and J. Seibert. 2006. On the calculation of the topographic wetness index: evaluation of different methods based on field observations. *Hydrology and Earth System Sciences* 10: 101–112. doi:10.5194/hess-10-101-2006.

de Sosa, L. L., H. C. Glanville, M. R. Marshall, A. Prysor Williams, and D. L. Jones. 2018. Quantifying the contribution of riparian soils to the provision of ecosystem services. *Science of the Total Environment*. doi:10.1016/j.scitotenv.2017.12.179.

Ståhl, G., A. Allard, P. A. Esseen, A. Glimskär, A. Ringvall, J. Svensson, S. Sundquist, P. Christensen, et al. 2011. National Inventory of Landscapes in Sweden (NILS)-scope, design, and experiences from establishing a multiscale biodiversity monitoring system. *Environmental Monitoring and Assessment* 173: 579–595. doi:10.1007/s10661-010-1406-7.

Tarboton, D. G. 1997. A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water Resources Research* 33: 309–319. doi:10.1029/96WR03137.

Tarboton, D. G., R. L. Bras, and I. Rodriguez-Iturbe. 1991. On the extraction of channel networks from digital elevation data. *Hydrological Processes* 5: 81–100. doi:10.1002/hyp.3360050107.

Tiwari, T., J. Lundström, L. Kuglerova, H. Laudon, K. Lidman, and A. M. Å gren. 2016. Cost of riparian buffer zones: A comparison of hydrologically adapted site-specific riparian buffers with traditional fixed widths. *Water Resources Research* 52: 1056–1069. doi:10.1002/2015WR018014.

Vaze, J., and J. Teng. 2007. Impact of DEM Resolution on Topographic Indices and Hydrological Modelling Results. Modsim 2007: *International Congress on Modelling and Simulation*: 706–712.

Voulvoulis, N., K. D. Arpon, and T. Giakoumis. 2017. The EU Water Framework Directive: From great expectations to problems with implementation. *Science of the Total Environment*. doi:10.1016/j.scitotenv.2016.09.228.

Wallin, M., A. Campeau, J. Audet, D. Bastviken, K. Bishop, J. Kokic, H. Laudon, E. Lundin, et al. 2018. Carbon dioxide and methane emissions of Swedish low-order streams-a national estimate and lessons learnt from more than a decade of observations. *Limnology and Oceanography Letters*. doi:10.1002/lol2.10061.

Popular science summary

Wet areas surrounding small streams are key habitats for many species of invertebrates, amphibians and plants and often used as dispersal corridors. These areas are sensitive to disturbance from forestry activities and special care needs to be taken to reduce negative impacts in these sensitive areas. Protective forested buffers are commonly used to protect streams during forest harvesting and wet areas should be protected from off road driving with heavy forestry machines. However this can be very difficult to do in practice since most small streams and wet areas are missing from current maps. The aim of this thesis was to evaluate and develop methods that can be used to map streams and wet areas so that they can receive better protection during forestry operations. To do this we used a three dimensional model of Sweden with a resolution of 2 m * 2 m. This three-dimensional landscape was used to determine where in the landscape water should accumulate. Once enough water has accumulated it transforms from being groundwater to surface water in the form of streams and wet areas. We used national databases of observed stream channels and wet areas to evaluate the accuracy of the artificial streams and wet areas and used machine learning to further improve the accuracy of the wet areas in particular. The modelled stream networks and maps of wet areas were more accurate than currently available maps and can be used to design hydrologically adapted protective zones around previously unmapped streams. Off road driving with heavy forestry machines can be planned to avoid damage to sensitive wet areas and streams.

Populärvetenskaplig sammanfattning

Fuktiga områden kring vattendrag är viktiga habitat för många arter av invertebrater, amfibier och växter. De fuktiga områdena fungerar även som spridningskorridorer för många arter och särskild hänsyn bör tas vid skogsbruk för att skydda dessa områden. Körskador i fuktig mark nära vattendrag har negativ påverkan på vattenkvalité i form av export av sediment och kvicksilver som påverkar nedströms ekosystem. En vanlig åtgärd är att lämna beskogade skyddszoner närmast vattendragen och undvika körning av tunga skogsmaskiner över fuktiga områden. Dessvärre så är det svårt att planera för dessa åtgärder i praktiken eftersom de allra flesta vattendrag och fuktiga områden helt enkelt saknas från dagens kartor. Syftet med den här avhandlingen har därför varit att utvärdera och utveckla metoder som kan användas för att kartlägga små vattendrag och fuktiga marker så de kan skyddas bättre vid skogsbruksåtgärder. För att göra det har vi använt en tredimensionell modell av Sverige där upplösningen är 2 m *2 m. Den här tredimensionella modellen användes för att avgöra var i landskapet ytligt grundvatten borde ackumuleras och när tillräckligt mycket vatten rinner till samma punkt i landskapet övergår det från att vara grundvatten till att bli ytvatten i form av små vattendrag. Därefter använder vi nationella databaser med fältdata för att utvärdera träffsäkerheten i de modellerade vattendragen och fuktiga markerna. Genom att kombinera olika modeller och befintliga kartor med hjälp av maskininlärning så ökade träffsäkerheten för fuktig mark ytterligare. Kartorna med modellerade vattendrag och fuktig mark hade högre träffsäkerhet än befintliga kartor och kan användas för att planera dynamiska skyddszoner kring tidigare okända vattendrag. Markfuktskartan kan användas för att planera körvägar för tunga skogsmaskiner för att undvika känsliga områden och på så sätt minska negativ inverkan på vattenkvalitet i vattendrag.

Acknowledgements

Firstly, I would like to express sincere gratitude to my advisor associate Professor Anneli Ågren for believing in me, motivating me and teaching me, even as her own life came crashing down on her. For her knowledge and shared love of the beauty of physical geography and GIS. For her superhuman speed to read and comment on manuscripts. Finally I'm grateful for her patient with my never ending side-projects.

Besides Anneli, I would like to thank Prof. Mats Nilsson for insightful comments and encouragement and for stepping up when needed. You always keep me in a good mood. My sincere thanks also goes to Prof. Tomas Lundmark for his support and random but inspirational chats. To Prof. Hjalmar Laudon for always being ready to help.

Thanks to the Forest agency in Gävleborg and the Swedish public employment service for collecting data on road culverts in Gävleborg and riparian zones in Norralaån.

I would also like to extend thanks my Canadian colleagues Prf. Dave Kreutzweiser, Dr. Erik Emilson for hiking around Black Brook and providing me with the data I needed. To Prof. Irena Creed for her support and help with data from Turkey lakes watershed. Special thanks to Dr John Lindsay and the team behind the Whitebox project. This thesis would not be possible without your amazing work.

I am grateful to everyone in the department of forest ecology and management and forest resource management, it's been a pleasure to have your around me. Special thanks to the Knights of the Round Table. You know who you are and you are all crazy.

I thank my older brother Jerry Lidberg for sparking my interest in gaming and his extensive knowledge on computer hardware. I am also grateful for Kim Lindgrens assistance with my coding problems. You both made this possible.

Also thank to the IT department of SLU. Probably the best IT department in the world.

Last but not the least, I would like to thank my family: both the Lidberg's and the Johansson's for supporting me throughout writing this thesis and my life in general. Especially to Jenny, Veija and Vinston for keeping balance and perspective in my life.

I

Received: 7 October 2016 | Accepted: 12 October 2017
DOI: 10.1002/hyp.11385

WILEY

RESEARCH ARTICLE

Evaluating preprocessing methods of digital elevation models for hydrological modelling

William Lidberg | Mats Nilsson | Tomas Lundmark | Anneli M. Ågren

Department of Forest Ecology and Management, Swedish University of Agricultural Sciences, Skogsmarksgränd, 901 83 Umeå, Sweden

Correspondence
William Lidberg, Department of Forest Ecology and Management, Swedish University of Agricultural Sciences, Skogsmarksgränd 901 83 Umeå, Sweden.
Email: william.lidberg@slu.se

Funding information
Kempe Foundation; VINNOVA; Swedish Energy Agency; EU Interreg program Water management in Baltic Forests (WAMBAF); Lilla Fonden för skogsvetenskaplig forskning, the Future Forest project (Mistra); ForWater Project (Formas)

Abstract
With the introduction of high-resolution digital elevation models, it is possible to use digital terrain analysis to extract small streams. In order to map streams correctly, it is necessary to remove errors and artificial sinks in the digital elevation models. This step is known as preprocessing and will allow water to move across a digital landscape. However, new challenges are introduced with increasing resolution because the effect of anthropogenic artefacts such as road embankments and bridges increases with increased resolution. These are problematic during the preprocessing step because they are elevated above the surrounding landscape and act as artificial dams. The aims of this study were to evaluate the effect of different preprocessing methods such as breaching and filling on digital elevation models with different resolutions (2, 4, 8, and 16 m) and to evaluate which preprocessing methods most accurately route water across road impoundments at actual culvert locations. A unique dataset with over 30,000 field-mapped road culverts was used to assess the accuracy of stream networks derived from digital elevation models using different preprocessing methods. Our results showed that the accuracy of stream networks increases with increasing resolution. Breaching created the most accurate stream networks on all resolutions, whereas filling was the least accurate. Burning streams from the topographic map across roads from the topographic map increased the accuracy for all methods and resolutions. In addition, the impact in terms of change in area and absolute volume between original and preprocessed digital elevation models was smaller for breaching than for filling. With the appropriate methods, it is possible to extract accurate stream networks from high-resolution digital elevation models with extensive road networks, thus providing forest managers with stream networks that can be used when planning operations in wet areas or areas near streams to prevent rutting, sediment transport, and mercury export.

KEYWORDS
breaching, culverts, digital elevation model, LiDAR, preprocessing, roads

1 | INTRODUCTION

In order to facilitate protection of surface waters, the first step is to map streams and lakes so protection can be incorporated in everyday land-use planning and management. Today's maps are often created from aerial photos; therefore, only streams distinguishable from aerial photos are displayed on current maps, which generate a bias towards larger streams. Also, because of canopy cover in forested landscapes, small forest streams are especially poorly mapped (Bishop et al., 2008; Kuglerová, Ågren, Jansson, & Laudon, 2014; Montgomery & Foufoula-Georgiou, 1993). In addition, streams that are present on current maps do not always form an integrated drainage network and do not change with seasons (Ågren, Lidberg, & Ring, 2015). Unless a stream is network based, it is not possible to trace water from each stream segment to the outlet of a catchment, and thus, managers are faced with a puzzle of different stream segments. Seasonal variations are also important because the length of stream networks changes dynamically between high and low flows (Ågren et al., 2015; Blyth & Rodda, 1973; Jones, 2000).

Recent advances in remote sensing and digital terrain analysis have paved the way for new techniques and better understanding of forest hydrology (Creed, Sass, Wolniewicz, & Devito, 2008; Murphy, Ogilvie, Castonguay et al., 2008; Ågren, Lidberg, Strömgren, Ogilvie, & Arp, 2014; Laudon et al., 2016). The better understanding of forest hydrology is partly due to the availability of better hydrological maps derived from high-resolution digital elevation models (DEMs) generated from Light Detection And Ranging (LiDAR; Murphy, Ogilvie, Castonguay et al., 2008). Early DEMs were created from photogrammetry, whereas modern DEMs are often derived from LiDAR point clouds and can have resolutions of less than 0.5 m × 0.5 m (a grid resolution of 0.5 m × 0.5 m will, from now on, be written as 0.5 m; Reutebuch, McGaughey, Andersen, & Carson, 2003). The amount of country-wide LiDAR datasets is rapidly increasing, and some examples of countries with a national DEM created from LiDAR are as follows: Denmark (Danish Geodata Agency), Finland (National Land Survey of Finland), and Sweden (Swedish Mapping, Cadastral and Land Registration Authority). These new DEMs are increasing in popularity amongst managers and are often used to map hydrological features such as stream networks (Vaze & Teng, 2007). Streams extracted from DEMs have three main advantages: First, they form an integrated drainage network (O'Callaghan & Mark, 1984); second, they are highly accurate (Goulden, Hopkinson, Jamieson, & Sterling, 2014) and follow actual channel depression in the DEM (Murphy, Ogilvie, Meng, & Arp, 2008); and third, they can easily be adjusted for seasonal variations and also display where ephemeral streams appear (Ågren et al., 2015).

Before any hydrological modelling can be applied to a DEM, it needs to be adjusted in order to be hydrologically correct (Jenson & Domingue, 1988; O'Callaghan & Mark, 1984). Water can only move downhill in a DEM, which means that sinks need to be removed to allow water to continue towards the outlet. Sinks are defined as areas surrounded by cells with higher elevations, which prevent water from moving further (Jenson & Domingue, 1988; Lindsay, 2015; Martz & Garbrecht, 1998; O'Callaghan & Mark, 1984; Zhang & Montgomery, 1994). They can be real depressions in the landscape or artefacts from urban features such as bridges. Thus, preprocessing of DEMs is important, especially because any errors in the input data will be amplified with each subsequent calculation (Kenward, Lettenmaier, Wood, & Fielding, 2000; Wise, 2000). There are two commonly used methods to handle sinks: filling (O'Callaghan & Mark, 1984; Wang & Liu, 2006) and breaching (Martz & Garbrecht, 1998; Martz & Garbrecht, 1999; Rieger, 1993). A fill algorithm examines the cells surrounding a sink and increases the elevation of the sink cells to match the lowest outlet cell (Planchon & Darboux, 2002; Wang & Liu, 2006). A breaching algorithm instead lowers the elevation of cells along a path between the lowest cell in the sink and the outlet of the sink (Martz & Garbrecht, 1998).

There are a number of studies that show how different preprocessing methods affect a DEM. Lindsay and Creed (2005) analysed the impact of the removal of artefact sinks from a 5-m DEM and found that methods combining filling and breaching had the least impact on the spatial and statistical distribution of terrain attributes. Poggio and Soille (2012) analysed the effect of preprocessing methods on stream networks and concluded that a combination of breaching and filling produced the most accurate stream network on a 30-m DEM. Lindsay (2015) demonstrated a flexible hybrid breaching–filling sink removal method on six large DEMs with resolutions of 30 and 90 m and concluded that the hybrid method performed similar to the highly efficient fill algorithm by (Wang & Liu, 2006) in terms of processing time. Preprocessing of high-resolution (<2 m) DEM introduces new challenges. There are mainly two problems associated with increasing the resolution of DEMs. The first problem is processing time, which increases drastically when the resolution increases and thus the number of data points increases (Barnes, Lehman, & Mulla, 2014; Qin & Zhan, 2012). The second problem is that features such as road–stream intersections become detectable, and, because roads are slightly elevated above surrounding terrain, they often appear to block the streams they cross. In reality, water may be draining underneath the road in a culvert or bridge (Shortridge, 2005).

Higher resolution also produces more detailed hydrographic features such as stream networks (Dehvari & Heck, 2013; Goulden et al., 2014; Vaze & Teng, 2007; Yang et al., 2014) but does not improve the detection of large features such as wetlands (Creed, Sanford, Beall, Molot, & Dillon, 2003) or topographic wetness index (Ågren et al., 2014). LiDAR is also sensitive to noise from low-lying vegetation and saturated soil surfaces, which need to be dealt with during the preprocessing (Goulden et al., 2014; Gyasi-Agyei, Willgoose, & Troch, 1995). An important advantage of high-resolution data is that it may contain information of forest ditching and similar small-scale features that impact drainage.

In the small country of Sweden, more than 210,000 km are forest roads built to extract timber from 227,000 km^2 of forested land. That equals roughly to 1 km of roads for every square kilometre of forest landscape. Ågren et al. (2015) mapped stream networks from a high-resolution DEM and found 2–5 km of streams per square kilometre of forested land, depending on season. This highlights the importance of handling sinks caused by road embankments correctly during the preprocessing stage; otherwise, the resulting hydrologically modelled maps will contain misplaced streams. The location of culverts needs to be incorporated into DEMs to prevent this error (Goulden et al., 2014; Shortridge, 2005). It can be done by breaching a path across roads if their locations are known, but this is rarely the case, and mapping culverts in the field is both time-consuming and costly. Much previous work has focused on coarser resolution DEM without small-scale anthropogenic features such as roads (Lindsay, 2015; Poggio & Soille, 2012); however, recent studies have addressed this problem (Lindsay & Dhun, 2015; Schwanghart, Groom, Kuhn, & Heckrath, 2013) using high-resolution data on small geographical areas.

In this study, we focus on digital terrain analysis to extract streams from DEMs with a range of different resolutions, in watersheds containing a large number of small-scale anthropogenic artefacts, which are mostly roads. The first research question in this study is, "Which preprocessing methods most accurately route water across road impoundments at actual culvert locations?" For this purpose, a large field inventory has been conducted in northern and central Sweden, where over 30,000 road culverts in 10 watersheds have been located and mapped manually. This is a unique dataset and a rare opportunity to evaluate the performance of preprocessing methods with focus on road impoundments.

We assume that one wants to enforce continuous flow to the outlet without losing important information from the original DEM. The second research question in this study is therefore, "How much of the landscape is affected by the different preprocessing methods?” Here, we evaluate area changed and the difference in absolute volume between original DEMs and preprocessed DEMs.

2 | MATERIALS AND METHODS

2.1 | Study sites

This study consists of nine large catchments in central Sweden (Gävleån, 2,458 km^2; Delångersån, 1,993 km^2; Harmångersån, 1,196 km^2; Testeboån, 1,111 km^2; Hamrångeån, 518 km^2; Skarjaån, 329 km^2; Norrlanån, 319 km^2; Gnarpsån, 229 km^2; and Ninån, 197 km^2) and one intermediate-sized catchment in northern Sweden (Krycklan, 68 km^2). When combined, the catchments cover 8,350 km^2, of which 82.3% are forested land, 8.7% are lakes and rivers, 6% are open land, 3.8% are agricultural land, and 0.3% are urban areas. The quaternary deposits in the catchments are dominated by till. All the large catchments have their outlets in the Baltic Sea, whereas Krycklan is a subcatchment to Vindeln River (Figure 1).

A culvert survey was conducted in Krycklan during June 29 to 25 July 25, 2013, where culvert locations were mapped using a handheld GPS with a horizontal accuracy < 10 m. These culverts were manually adjusted using a 0.5-m DEM and a 17-cm Orto photo in order to increase the precision. The culvert surveys of the larger catchments were conducted in collaboration with the Swedish Forest Agency during the snow-free periods of 2014–2015 using a handheld GPS with a horizontal accuracy of 0.3 m. A total of 30,883 culverts were mapped during the field surveys. Densely populated urban areas with underground drainage systems were excluded from the survey (0.3% of the combined area). This study uses the Swedish National DEM generated by the Swedish Mapping, Cadastral and Land Registration Authority using LiDAR. This DEM has a cell resolution of 2 m and was generated from a point cloud with a point density of 0.5–1 points/m^2 with horizontal and vertical errors of 0.1 and 0.3 m, respectively. This DEM was resampled using nearest-neighbour interpolation to 4-, 8-, and 16-m DEMs.

The preprocessing methods that have been evaluated can be sorted into three categories: algorithms that fill sinks, algorithms that breach sinks, and algorithms that utilize a combination of both filling and breaching to remove sinks. In this study, we focus on efficient algorithms capable of handling large DEMs (~1,000 km^2 at 2-m resolution). The following is a short introduction to the evaluated algorithms. Each method is given a short name in this study (in italics), and all methods are summarized in Table 1.

2.2 | Fill algorithms (also known as incremental methods)

Wang and Liu (2006) introduced the priority flood algorithm, which examines each cell on the basis of its spill elevation, starting from the edge cells, and visiting cells from lowest order using a priority queue. This algorithm was modified to work with larger LiDAR DEMs and implemented in SAGA

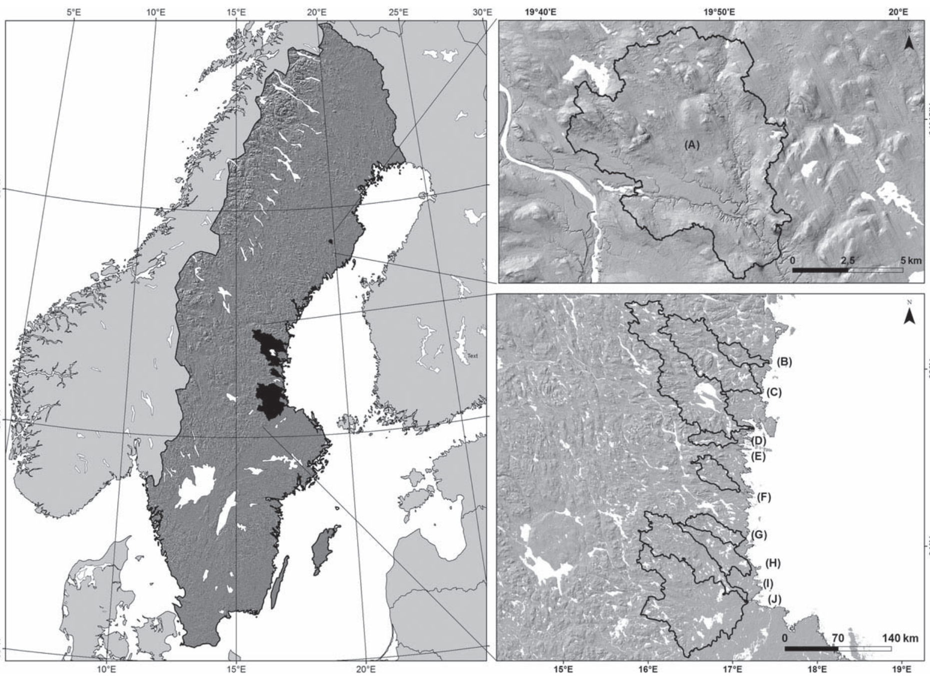

FIGURE 1 The nine large catchments are located along the coast of central Sweden, whereas the small catchment is 60 km inland in northern Sweden. (A) Krycklan, (B) Gnarpsån, (C) Harmångersån, (D) Delångersån, (E) Nianån, (F) Norralanån, (G) Skårjån, (H) Hamrångeån, (I) Testeboån, and (J) Gåvleån

TABLE 1 The evaluated methods are summarized on the left, using the same name as the main text

Name	Description	Program
Fill	Fill with flat increment[a]	Whitebox GAT
BR fill	BR[b] + Fill with flat increment[a]	Whitebox GAT
LCAT breach	Least cost auxiliary topography	TopoToolbox
BR LCAT breach	BR[b] + Least cost auxiliary topography	TopoToolbox
Complete breach	Complete breaching mode[c]	GoSpatial
BR complete breach	BR[b] + Complete breaching mode[c]	GoSpatial
Constrained breach	Constrained breaching mode[d]	GoSpatial
BR constrained breach	BR[b] + Constrained breaching mode[d]	GoSpatial
Selective breach	Selective breaching mode[e]	GoSpatial
BR selective breach	BR[b] + Selective breaching mode[e]	GoSpatial

Note. The descriptions show how each method was run and is further explained below. The programs used to run each method are displayed on the right.

[a]Flat increment = Flats were given the arbitrary slope of 0.001°.

[b]BR = Streams were burned across roads with a maximum length of 50 m.

[c]Complete breaching mode = All sinks were resolved by breaching.

[d]Constrained breaching mode = 2 m max depth, 50 grid cells length followed by internal breaching and fill.

[e]Selective breaching mode = 2 m max depth, 50 grid cells length followed by fill.

GIS 2.2 and Whitebox GAT 3.4 and can be set to add a small elevation increment to flat area cells to impose a flow direction. An increment of 0.001° was chosen for this study and will be referred to as *fill*.

2.3 | Breaching algorithms (also known as decremental methods)

The first breaching methods were introduced by Martz and Garbrecht (1998) and Rieger (1993, 1998) and worked by identifying and breaching the lowest outflow in a sink if specific criteria of depth and breach length were meet. Studies by Soille (2004), Schwanghart and Kuhn (2010), and Schwanghart et al. (2013) propose breach algorithms based on the least cost auxiliary topography. This algorithm is included in MATLAB TopoToolbox R2013b and will be referred to as *LCAT breach*. An even more efficient breaching algorithm was introduced by Lindsay (2015) and is available in a small program called GoSpatial. This method will be referred to as *complete breach*.

2.4 | Hybrid algorithms (incremental and decremental combined)

GoSpatial also offers the possibility to combine breaching and filling into a hybrid solution using a priority flood algorithm where sinks can be resolved by *selective* or *constrained* breaching. Constrained breach and selective breach was run with a maximum breach length of 50 grid cells and maximum breach depth of 2 m. This means that sinks that would require a breaching path of more than 50 grid cells or sinks deeper than 2 m will be filled instead of breached. The main difference between constrained and selective breach is that selective breaching does not breach sinks that do not meet the criteria above, whereas constrained breaching creates a partial breach up to the above-defined criteria in order to reduce the interior sink size (Lindsay, 2015). For example, constrained breaching will breach a channel of 50 m before applying fill, whereas selective breaching will stop and fill without breaching that specific sink.

There is also an option to burn a known stream network into a DEM. Unfortunately, forest hydrology is often poorly mapped, and only streams distinguishable from aerial photos are displayed on current maps, which makes stream burning questionable (Lindsay & Dhun, 2015). Even so, it is still reasonable to assume that the location of a stream–road crossing would be easier to distinguish from aerial photos because of the opening in the canopy along roads, making these locations more reliable. Therefore, streams from existing maps were burned into the DEM where they crossed a road, and only a short distance (maximum 50 m) that would correspond to the distance necessary to burn across the largest road embankments in the catchments. This step was done using the tool "burn streams at roads" in Whitebox GAT and will be referred to as "BR." Here we applied (*fill*, *complete breach*, *selective breach*, *constrained breach*, and *LCAT*) separately to the stream–road-burned DEM. Methods where the stream–road intersections were burned into the DEM have "BR" added to the name to clarify this (*BR fill*, *BR complete breach*, *BR constrained breach*, *BR selective breach*, and *BR LCAT*).

2.5 | Evaluation

Field mapping an entire stream network is not an easy task, and stream networks are tricky to compare in a reliable way (Molloy & Stepinski, 2007). Instead of comparing the entire stream network, we focus on locations where streams intersect roads. Our unique dataset of field-mapped culvert locations allows us to investigate if the modelled stream network crosses the road at the correct locations, that is, where the stream drains underneath the road in a culvert. For this assessment, stream networks were extracted from each preprocessed DEM using the flow routing algorithm Deterministic-8 (O'Callaghan & Mark, 1984) and a flow initiation threshold or accumulated area (Tarboton, Bras, & Rodriguez-Iturbe, 1991) of 0.02 km^2 (2 ha), which represents spring flood on the basis of field observations of stream initiation in the northernmost study catchment (the Krycklan catchment; Ågren et al., 2015). This means that culverts located in areas near a water divide, before a stream has been initiated, will not be intersected by this stream network. A lower flow initiation threshold would produce a more extensive stream network and intersect more of the field-mapped culverts, but we decided that it would be more relevant to use a realistic flow initiation. A stream–road intersection was only considered to be accurate if a stream passed within 10 m of both ends of a culvert. The 10-m search radius was chosen to avoid nearby culverts at road intersections and similar locations.

2.6 | Effects of preprocessing methods on DEMs

Preprocessed DEMs were compared to original DEMs in order to analyse how preprocessing methods changed the DEM. This comparison included area changed and absolute volume changed, which are commonly used to assess the impact of preprocessing methods (Lindsay & Creed, 2005; Poggio & Soille, 2012). Absolute volume change is the sum of the absolute height difference for all cells in the catchment before and after the preprocessing multiplied by the total number of cells (Equation 1).

$$\mathrm{Abs(volume)} = a \sum_{i=1}^{N} \left(z_{i,\mathrm{orig}} - z_{i,\mathrm{proc}} \right). \tag{1}$$

a is the area of a raster cell, $z_{i,\mathrm{orig}}$ is the elevation for raster cell i in the original DEM, $z_{i,\mathrm{proc}}$ is the elevation for raster cell i in the preprocessed DEM, and N is the number of raster cells in the DEM.

LiDAR is absorbed by water, so elevation data in these surfaces were interpolated from surrounding terrain during the DEM creation. They were also flattened using lake and river polygons from a topographical map and given an arbitrary slope towards the coast. These areas were excluded from the evaluation of preprocessing methods impact on the DEMs.

3 | RESULT

3.1 | Correct stream–road crossings

Stream networks from all preprocessed DEMs were intersected with over 30,000 field-mapped road culverts, and the number of correct

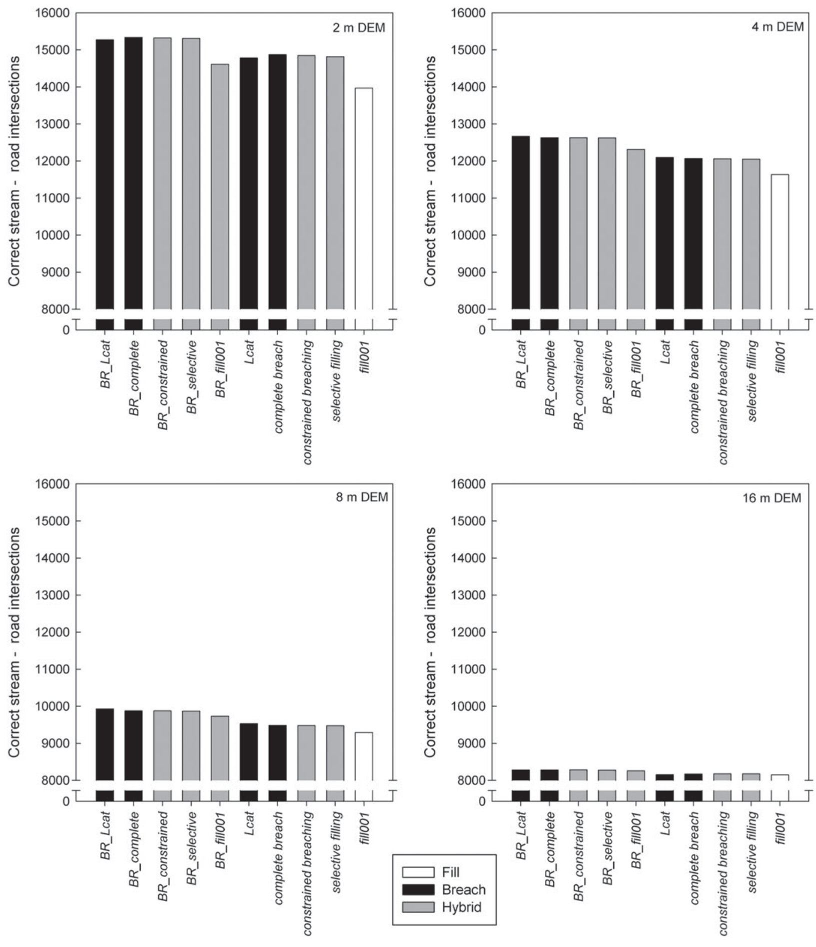

FIGURE 2 The accuracy of topographically derived stream networks increases with increasing digital elevation model (DEM) resolution. Preprocessing methods that prioritize breaching over filling lead to more accurate stream networks on all DEM resolutions

stream–road crossings was used to evaluate accuracy of each method. The accuracy of topographically derived stream networks increased with increasing DEM resolution. Stream networks from the 2-m DEM intersected roughly twice the number of culverts as stream networks from the 16-m DEM. Further, preprocessing methods that prioritized breaching over filling lead to more accurate stream networks on all DEM resolutions (Figure 2). The difference between breaching and filling increased with increasing resolution. Burning streams from the topographic map across roads from the topographic map (*BR*), before applying a complete preprocessing method, increased the number of correct stream–road crossings for all methods, especially for filling. This step was sensitive to scale, and the effect increased with increasing DEM resolution. The least cost auxiliary topography breaching method (*BR LCAT*) intersected most culverts on all DEM resolutions, which means that stream networks extracted from the 2-m DEM preprocessed by *BR LCAT* were most accurate in this study. *BR complete breach*, *BR constrained breach*, and *BR selective breach* also performed well, whereas *fill* had the least amount of correct stream–road crossings on all resolutions.

3.2 | Preprocessing effects on DEMs

The impact of each method was defined by changes in DEM area and absolute volume between the original DEMs and the preprocessed DEMs. Methods that prioritized breach over fill made the least changes, to both area and absolute volume (Figure 3). This was the case for all resolutions. All methods changed larger areas on higher resolution DEMs, especially fill. The difference in area changed between methods that prioritize breaching and methods that prioritize filling also increased with increasing DEM resolution. Burning streams from the topographic map across roads from the topographic map (BR), before applying another preprocess method, reduced the change in area for all methods on the 2- and 4-m DEMs but had little effect on the 8- and 16-m DEMs. Changes to absolute volume decreased with increasing resolution for pure breaching methods, whereas hybrid and filling methods made the most changes to absolute volume on the 2-m DEM. *BR LCAT* and *LCAT* made the least changes on DEM area, whereas *BR complete breach* and *complete breach* made the least changes to absolute volume regardless of DEM resolution. *Fill* and *BR fill* had the biggest impact on both area and absolute volume on all resolutions.

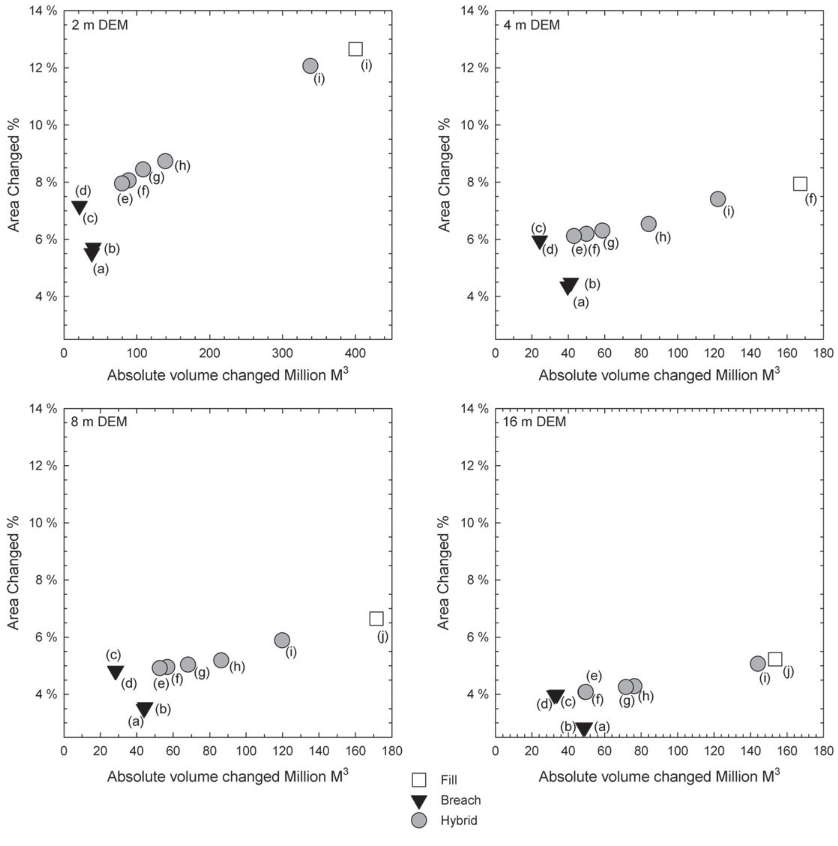

FIGURE 3 Change in absolute volume of the digital elevation models in Million M^3 against changed area in percent of total area. (a) BR LCAT, (b) LCAT, (c) BR complete breach, (d) complete breach, (e) BR constrained, (f) constrained, (g) BR selective, (h) selective breach (i) BR fill, and (j) fill

4 | DISCUSSION

In this study, we assessed different methods to preprocess DEMs of varying resolutions by analysing the number of field-mapped culverts intersected by extracted stream networks. The effect of each preprocessing method was assessed by area changed, and absolute volume changed, from the original DEMs. Our results showed that the least cost auxiliary topography method proposed by Schwanghart and Kuhn (2010) and Schwanghart et al. (2013) (*LCAT*) was the most accurate in terms of number of culverts intersected, regardless of DEM resolution. We also found that the accuracy increased when streams from the topographic map were burned across roads from the topographical map, before applying a complete preprocessing method. In this study, a stream–road intersection was only considered to be accurate if a stream passed within 10 m of both ends of a culvert. Using a 10-m search radius for all resolutions allows for a more direct comparison between resolutions, but it can potentially cause some issues with the 8- and 16-m DEMs because the nodes of the extracted stream network are located in the centre of the resampled grid cells.

Increasing resolution also increased the accuracy in terms of number of correct stream–road crossings. This is consistent with a study in Canada where Goulden et al. (2014) evaluated stream networks delineated from 1-, 5-, 10-, 15-, and 50-m DEMs and concluded that stream networks from the 1-m DEM produced the highest spatial accuracy. Dehvari and Heck (2013) did a similar study in Canada and observed large differences between 1 m and 10 m DEMs on all topographical and hydrological attributes, suggesting that 10 m might be to course to extract streams in that landscape.

Increasing DEM resolution increased the area affected by preprocessing, especially for methods that prioritize fill. This is likely due to sinks caused by small-scale features, which become visible at higher resolutions. Features such as road embankments could explain increasing differences in area changed, and number of correct stream–road crossings, between breaching and filling at higher resolutions. *BR LCAT* created the most accurate stream network, and it changed 52% less of the study area compared to the classic fill method on the 2-m DEM. This is also consistent with recent findings. Lindsay and Dhun (2015) evaluated preprocessing algorithms on a 1-m DEM in a landscape dominated by agriculture and found that breaching changed an area 86.5% smaller than filling. This is consistent with results from a study on a 30-m DEM by Poggio and Soille (2012). Some of the difference in impact between filling and breaching can be attributed to flat areas in our catchments. If a road crosses the outlet of a flat area, the fill algorithms will fill up the whole area in order to remove the sink, whereas breach algorithms will breach a channel across the road. Burning streams from the topographic map, across roads from the topographic map, reduced the impact on the DEMs and improved the accuracy for all methods but especially for filling methods. This shows just how sensitive filling is to road embankments.

Previous studies have shown that methods that change the DEM less produces more accurate stream networks (Lindsay & Creed, 2005; Poggio & Soille, 2012). This is consistent with our results, but there is no reason why minimizing the impact should be a goal by itself. The aim of any preprocessing method is to create accurate flow directions and by extension accurate stream networks. One of the most important advantages with breaching instead of the filling used here is the behaviour of flow paths upstream of a road embankment. Streams from both methods might cross the road in a correct location, but fill will produce straight parallel streams across the filled area, whereas breach uses the flow path information of the unfilled DEM to the beaching point. This means that filling fails to utilize information about flow directions in the filled areas (Figure 4).

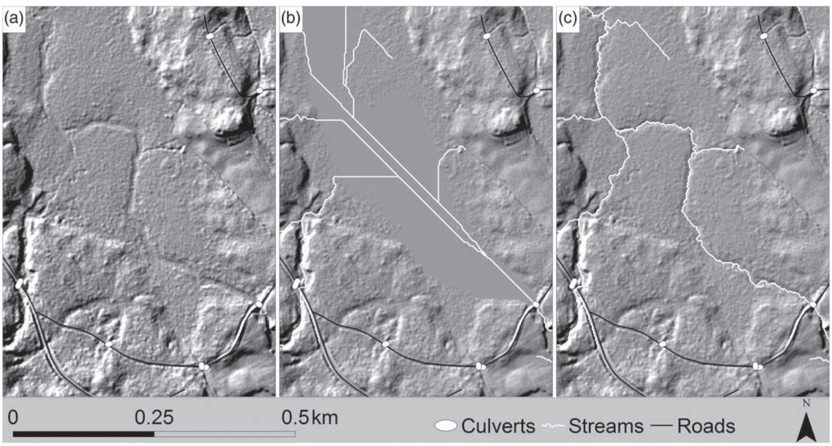

FIGURE 4 One of the most important differences between filling and breaching is not where they cross a road but rather how they affect the upstream flow paths. (a) The road embankment in the bottom right corner is creating a sink at the stream–road intersection. A stream channel is visible in the original digital elevation model. (b) Filling creates a flat area of arbitrary values upstream of the road embankment, which results in parallel and unrealistic stream segments. (c) Breach, on the other hand, manages to utilize the flow path information of the area upstream of the road embankment

However, there are other filling methods such as the one described by Martz and Garbrecht (1998) that impose convergent flow paths away from a higher elevation towards a lower elevation. Selective filling and constrained breaching give the user the option to choose which sinks to fill or breach. Optimally, very deep sinks, such as quarries, should be filled, whereas road embankments and bridges should be breached (Lindsay, 2015). This was especially important on the high-resolution DEMs in this study because our catchments contained a large number of road embankments, which means that there were many sinks that should be solved by breaching. If most sinks were caused by artificial sinks from open mines and quarries, instead of artificial embankments, it is likely that filling would be a preferred method. Selective filling or constrained breaching might be preferable if the DEM contains both deep sinks and road embankments. Selecting appropriate thresholds for maximum breach depth and length can be difficult and will vary with resolution because the origin of sinks changes with resolution.

Road embankments, bridges, and culverts are some of the biggest issue to address in order to create reliable stream networks from high-resolution LiDAR DEMs (Schwanghart et al., 2013). One advantage with high-resolution LiDAR DEMs is that they might contain information about small-scale anthropogenic features such as ditches that can be incorporated in the hydrological models in order to improve the accuracy of stream networks. This would allow us to shed some light on the unknown headwaters described by Bishop et al. (2008). Forest managers could use these stream networks to better plan operations in wet areas near streams in order to prevent rutting (Ågren et al., 2015) and subsequent sediment transport (Kreutzweiser & Capell, 2001) and mercury export (Munthe & Hultberg, 2004).

5 | CONCLUSIONS

The accuracy of stream networks, in terms of correct culvert intersections, increased with increasing DEM resolution. Stream networks extracted from DEMs that had been breached instead of filled created more accurate stream networks on all resolutions and had less impact in terms of change to area and absolute volume. The difference in accuracy between breaching and filling increased with increasing resolution. The accuracy also increased when streams from the topographic map were burned across roads from the topographical map, for all methods and resolutions.

ACKNOWLEDGMENTS

Big thanks to the personnel at the Swedish Forest Agency who conducted the field survey for the five large study catchments. The research was financed by the Swedish Energy Agency, VINNOVA, the Kempe Foundation, the EU Interreg program Water management in Baltic Forests (WAMBAF), Lilla Fonden för skogsvetenskaplig forskning, the Future Forest project (Mistra), and the ForWater Project (Formas). We also like to thank KUA Foundation Gävleborg; County Administrative Board in Gävleborg; Arbetsförmedlingen in Gävleborg; and the Swedish Mapping, Cadastral and Land Registration Authority in Gävleborg.

ORCID

William Lidberg http://orcid.org/0000-0001-5780-5596
Mats Nilsson http://orcid.org/0000-0001-7394-6305
Tomas Lundmark http://orcid.org/0000-0003-2271-3469
Anneli M. Ågren http://orcid.org/0000-0002-6758-3971

REFERENCES

Ågren, A. M., Lidberg, W., Strömgren, M., Ogilvie, J., & Arp, P. A. (2014). Evaluating digital terrain indices for soil wetness mapping—A Swedish case study. *Hydrology and Earth System Sciences*, *18*(9), 3623–3634. https://doi.org/10.5194/hess-18-3623-2014

Ågren, M. A., Lidberg, W., & Ring, E. (2015). Mapping temporal dynamics in a forest stream network—Implications for riparian forest management. *Forests*, *6*(9), 2982–3001. https://doi.org/10.3390/f6092982

Barnes, R., Lehman, C., & Mulla, D. (2014). Priority-flood: An optimal depression-filling and watershed-labeling algorithm for digital elevation models. *Computers & Geosciences*, *62*, 117–127. https://doi.org/10.1016/j.cageo.2013.04.024

Bishop, K., Buffam, I., Erlandsson, M., Folster, J., Laudon, H., Seibert, J., & Temnerud, J. (2008). Aqua Incognita: The unknown headwaters. *Hydrological Processes*, *22*(8), 1239–1242. https://doi.org/10.1002/hyp.7049

Blyth, K., & Rodda, J. C. (1973). A stream length study. *Water Resources Research*, *9*(5), 1454–1461. https://doi.org/10.1029/WR009i005p01454

Creed, I. F., Sanford, S. E., Beall, F. D., Molot, L. A., & Dillon, P. J. (2003). Cryptic wetlands: Integrating hidden wetlands in regression models of the export of dissolved organic carbon from forested landscapes. *Hydrological Processes*, *17*(18), 3629–3648. https://doi.org/10.1002/hyp.1357

Creed, I. F., Sass, G. Z., Wolniewicz, M. B., & Devito, K. J. (2008). Incorporating hydrologic dynamics into buffer strip design on the sub-humid boreal plain of Alberta. *Forest Ecology and Management*, *256*(11), 1984–1994. https://doi.org/10.1016/j.foreco.2008.07.021

Dehvari, A., & Heck, R. J. (2013). Effect of LiDAR derived DEM resolution on terrain attributes, stream characterization and watershed delineation. *International Journal of Agriculture and Crop Sciences (IJACS) 6* (13): 949–967: 2227-670X

Goulden, T., Hopkinson, C., Jamieson, R., & Sterling, S. (2014). Sensitivity of watershed attributes to spatial resolution and interpolation method of LiDAR DEMs in three distinct landscapes. *Water Resources Research*, *50*(3), 1908–1927. https://doi.org/10.1002/2013WR013846

Gyasi-Agyei, Y., Willgoose, G., & Troch, F. P. (1995). Effects of vertical resolution and map scale of digital elevation models on geomorphological parameters used in hydrology. *Hydrological Processes*, *9*(3–4), 363–382. https://doi.org/10.1002/hyp.3360090310

Jenson, S. K., & Domingue, J. O. (1988). Extracting topographic structure from digital elevation data for geographic information-system analysis. *Photogrammetric Engineering and Remote Sensing 54* (11): 1593–1600: 0099–1112

Jones, J. A. (2000). Hydrologic processes and peak discharge response to forest removal, regrowth, and roads in 10 small experimental basins, western cascades, Oregon. *Water Resources Research*, *36*(9), 2621–2642. https://doi.org/10.1029/2000WR900105

Kenward, T., Lettenmaier, D. P., Wood, E. F., & Fielding, E. (2000). Effects of digital elevation model accuracy on hydrologic predictions. *Remote Sensing of Environment*, *74*(3), 432–444. https://doi.org/10.1016/S0034-4257(00)00136-X

Kreutzweiser, D. P., & Capell, S. S. (2001). Fine sediment deposition in streams after selective forest harvesting without riparian buffers. *Canadian Journal of Forest Research*, *31*(12), 2134–2142. https://doi.org/10.1139/x02-086

Kuglerová, L., Ågren, A., Jansson, R., & Laudon, H. (2014). Towards optimizing riparian buffer zones: Ecological and biogeochemical implications for forest management. *Forest Ecology and Management*, *334*(0), 74–84. https://doi.org/10.1016/j.foreco.2014.08.033

Laudon, H., Kuglerova, L., Sponseller, R. A., Futter, M., Nordin, A., Bishop, K., … Ågren, A. M. (2016). The role of biogeochemical hotspots, landscape heterogeneity, and hydrological connectivity for minimizing forestry effects on water quality. *Ambio*: 11: DOI https://doi.org/10.1007/s13280-015-0751-8

Lindsay, J. B. (2015). Efficient hybrid breaching–filling sink removalmethods for flow path enforcement in digitalelevation models. *Hydrological Processes*, *21*. https://doi.org/10.1002/hyp.10.1002/hyp.10648

Lindsay, J. B., & Creed, I. F. (2005). Removal of artifact depressions from digital elevation models: Towards a minimum impact approach. *Hydrological Processes*, *19*(16), 3113–3126. https://doi.org/10.1002/hyp.5835

Lindsay, J. B., & Dhun, K. (2015). Modelling surface drainage patterns in altered landscapes using LiDAR. *International Journal of Geographical Information Science*, *29*(3), 397–411. https://doi.org/10.1080/13658816.2014.975715

Martz, L. W., & Garbrecht, J. (1998). The treatment of flat areas and depressions in automated drainage analysis of raster digital elevation models. *Hydrological Processes*, *12*(6), 843–855. https://doi.org/10.1002/(SICI)1099-1085(199805)12:6%3C843::AID-HYP658%3E3.0.CO;2-R

Martz, L. W., & Garbrecht, J. (1999). An outlet breaching algorithm for the treatment of closed depressions in a raster DEM. *Computers & Geosciences*, *25*(7), 835–844. https://doi.org/10.1016/S0098-3004(99)00018-7

Molloy, I., & Stepinski, T. F. (2007). Automatic mapping of valley networks on Mars. *Computers & Geosciences*, *33*(6), 728–738. https://doi.org/10.1016/j.cageo.2006.09.009

Montgomery, D. R., & Foufoula-Georgiou, E. (1993). Channel network source representation using digital elevation models. *Water Resources Research*, *29*(12), 3925–3934. https://doi.org/10.1029/93WR02463

Munthe, J., & Hultberg, H. (2004). Mercury and methylmercury in runoff from a forested catchment—Concentrations, fluxes, and their response to manipulations. *Water, Air, & Soil Pollution: Focus*, *4*(2–3), 607–618. https://doi.org/10.1023/B:WAFO.0000028381.04393.ed

Murphy, P. N. C., Ogilvie, J., Castonguay, M., Zhang, C. F., Meng, F. R., & Arp, P. A. (2008). Improving forest operations planning through high-resolution flow-channel and wet-areas mapping. *Forestry Chronicle*, *84*(4), 568–574. https://doi.org/10.5558/tfc84568-4

Murphy, P. N. C., Ogilvie, J., Meng, F., & Arp, P. (2008). Stream network modelling using lidar and photogrammetric digital elevation models: A comparison and field verification. *Hydrological Processes*, *22*(August 2007), 1747–1754. https://doi.org/10.1002/hyp

O'Callaghan, J. F., & Mark, D. M. (1984). The extraction of drainage networks from digital elevation data. *Computer Vision Graphics and Image Processing*, *28*(3), 323–344. https://doi.org/10.1016/S0734-189x(84)80011-0

Planchon, O., & Darboux, F. (2002). A fast, simple and versatile algorithm to fill the depressions of digital elevation models. *Catena*, *46*(2001), 159–176. https://doi.org/10.1016/S0341-8162(01)00164-3

Poggio, L., & Soille, P. (2012). Influence of pit removal methods on river network position. *Hydrological Processes*, *26*(13), 1984–1990. https://doi.org/10.1002/Hyp.8290

Qin, C. Z., & Zhan, L. J. (2012). Parallelizing flow-accumulation calculations on graphics processing units—From iterative DEM preprocessing algorithm to recursive multiple-flow-direction algorithm. *Computers & Geosciences*, *43*, 7–16. https://doi.org/10.1016/j.cageo.2012.02.022

Reutebuch, S. E., McGaughey, R. J., Andersen, H. E., & Carson, W. W. (2003). Accuracy of a high-resolution lidar terrain model under a conifer forest canopy. *Canadian Journal of Remote Sensing*, *29*(5), 527–535. https://doi.org/10.5589/m03-022

Rieger, W. (1993). Automated river line and catchment area extraction from DEM data. *Int. Arch.Photogramm.Remote Sens.*, *29*, 642–642.

Rieger, W. (1998). A phenomenon-based approach to upslope contributing area and depressions in DEMs. *Hydrological Processes*, *12*(6), 857–872. https://doi.org/10.1002/(Sici)1099-1085(199805)12:6%3C857::Aid-Hyp659%3E3.3.Co;2-2

Schwanghart, W., Groom, G., Kuhn, N. J., & Heckrath, G. (2013). Flow network derivation from a high resolution DEM in a low relief, agrarian landscape. *Earth Surface Processes and Landforms*, *38*(13), 1576–1586. https://doi.org/10.1002/esp.3452

Schwanghart, W., & Kuhn, N. J. (2010). TopoToolbox: A set of Matlab functions for topographic analysis. *Environmental Modelling & Software*, *25*(6), 770–781. https://doi.org/10.1016/j.envsoft.2009.12.002

Shortridge, C. P. B. A. (2005). Lidar elevation data for surface hydrologic modeling: Resolution and representation issues. *Cartography and Geographic Information Science*, *32*(4), 401–410. https://doi.org/10.1559/152304005775194692

Soille, P. (2004). Morphological carving. *Pattern Recognition Letters 25* (5): 543–550 Available DOI: https://doi.org/10.1016/j.patrec.2003.12.007

Tarboton, D. G., Bras, R. L., & Rodriguez-Iturbe, I. (1991). On the extraction of channel networks from digital elevation data. *Hydrological Processes*, *5*(1), 81–100. https://doi.org/10.1002/hyp.3360050107

Vaze, J., & Teng, J. (2007). Impact of DEM resolution on topographic indices and hydrological Modelling results. Modsim 2007. *International Congress on Modelling and Simulation*, 706–712. https://doi.org/10.1016/j.envsoft.2010.03.014

Wang, L., & Liu, H. (2006). An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modelling. *International Journal of Geographical Information Science*, *20*(2), 193–213. https://doi.org/10.1080/13658810500433453

Wise, S. (2000). Assessing the quality for hydrological applications of digital elevation models derived from contours. *Hydrological Processes*, *14*(11–12), 1909–1929. https://doi.org/10.1002/1099-1085(20000815/30)14:11/12%3C1909::AID-HYP45%3E3.0.CO;2-6

Yang, P., Ames, D. P., Fonseca, A., Anderson, D., Shrestha, R., Glenn, N. F., & Cao, Y. (2014). What is the effect of LiDAR-derived DEM resolution on large-scale watershed model results? *Environmental Modelling & Software*, *58*, 48–57. https://doi.org/10.1016/j.envsoft.2014.04.005

Zhang, W. H., & Montgomery, D. R. (1994). Digital elevation model grid size, landscape representation, and hydrologic simulations. *Water Resources Research*, *30*(4), 1019–1028. https://doi.org/10.1029/93WR03553

How to cite this article: Lidberg W, Nilsson M, Lundmark T, Ågren AM. Evaluating preprocessing methods of digital elevation models for hydrological modelling. *Hydrological Processes*. 2017;31:4660–4668. https://doi.org/10.1002/hyp.11385

II

The importance of better mapping of stream networks using high resolution digital elevation models. Upscaling from watershed scale to regional and national scales.

Anneli M. Ågren, William Lidberg*
Swedish University of Agricultural Science, Department Forest Ecology and Management, S-90183 Umeå, Sweden

Manuscript

*Corresponding author

Abstract

Headwaters make up the majority of any given stream network, yet, they are poorly mapped. A solution to this is to model stream networks from a high resolution digital elevation model. Selecting the correct stream initiation threshold is key, but how do you do that on a national scale across physiographic regions? Here the Swedish landscape is used as a test bench to investigate how mapping of small stream channels (<6 m width) can be improved. The best modelled stream channel network was generated by pre-processing the DEM, calculating accumulated flow, and extracting stream networks using a stream initiation threshold of 2 ha. The Matthews Correlation Coefficient (MCC) for the 2 ha stream channel network was 0.463 while the best available maps of today, the Swedish property map (1:12 500) had an MCC of 0.387.

A residual analysis of the 2 ha network show that there is additional improvements to be made by adapting the model to local conditions, as 15% of the over and underestimation could be explained by the variability in runoff, quaternary deposits, local topography and location. The most accurate stream channel network had a length 4.5 times longer the currently mapped stream network, demonstrating how important accurate stream networks is for upscaling aquatic and climate research.

Keywords: Stream network, Stream mapping, digital elevation model, LiDAR, Headwater streams

1 Introduction

Headwaters dominate surface water drainage networks and studies of headwater catchments have provided understanding of different sources and controls on biogeochemistry in streams (Seibert et al. 2009; Tiwari et al. 2017), and also interactions with the atmosphere (Natchimuthu et al. 2017; Wallin et al. 2013). Despite the importance of headwaters, it's a paradox that at the same time small headwaters can be called Aqua Incognita (Bishop et al. 2008; Kuglerová et al. 2017), a relevant term as the majority of headwater streams are poorly mapped. Maps have traditionally been constructed from aerial photos, but small stream channels are difficult to observe from the air, especially under a dense tree canopy. Hence there is a bias on maps that show larger streams, and streams in agricultural areas where trees are scarce, while smaller streams are missing. Even the best available map for Sweden (the 1:12 500 property map), will therefore severely underestimate the total length of stream networks. This can have repercussions for research questions such as process understanding and budgets. For example, in the Krycklan Study Catchment (Laudon et al. 2013) it was shown that CO_2 evasions was high from small scale streams, 72% of the CO_2 was evaded to the atmosphere from 1st to 2nd order streams (Wallin et al. 2013). Wallin et al. (2018) highlighted the importance of low order headwater streams by estimating CO_2 emissions from a 400 000 km stream network that was based on a 50*50 m digital elevation model. They concluded that low order headwater streams emitted CO_2 corresponding to 21% of the estimated terrestrial C sequestration. Benstead and Leigh (2012) estimated that global estimates of CO_2 evasion from streams would increase from 0.56 Pg C yr^{-1} to 1.6 Pg C yr^{-1} if one assumes a 50% increase in area of small rivers (1st to 5th order).

Headwater streams have a high amount of stream edge relative to stream surface area (Richardson and Danehy 2007) and local ground water discharge is a major contributor to water flow in these streams (Leach et al. 2017). Therefore headwater streams and their riparian zones constitutes an interface between water and soil, and largely control inputs from surrounding landscapes to downstream ecosystems (Lidman et al. 2017). They also provide important ecosystem services such as cycling nutrients (Blackburn et al. 2017; Bormann and Likens 1967) and buffering impact of pollutants (Klaminder et al. 2006). Headwater streams also function as important habitat for both invertebrates and plants and functions as migration corridors (Freeman et al. 2007). This strong coupling between soils and streams brings up important issues regarding management of small streams. Any perturbation in headwaters will affect downstream environments, so in order to protect large streams, it's important to protect the headwater streams (Kuglerová et al. 2017; Wipfli et al. 2007).

In order to give small streams good protection, the first step is to know where they are. Topographical modelling using digital elevation models (DEM) is a commonly used method to map streams (Jaeger et al. 2019; González-Ferreras and Barquín 2017; Julian et al. 2012) and high resolution DEMS derived from airborne light detection and ranging (LiDAR) can be used to map even the smallest streams (Goulden et al. 2014). Some advantages with this approach is that modelled stream networks form integrated drainage networks (Vaze and Teng 2007) and follow channel depressions (Murphy et al. 2008b). There are however some problems with this approach. First, high resolution DEMs contains artificial features such as roads and require pre-processing to become hydrologically correct (Lindsay and Creed 2005). Secondly is to define appropriate stream initiation thresholds. This threshold is the minimum catchment area required for groundwater to become surface water and form a stream. This threshold regulates how extensive a stream network is and often require area specific knowledge or field data to make educated guesses. There are a number of studies where stream heads (Ågren et al. 2015; Avcioglu et al. 2017; Imaizumi et al. 2010; McNamara et al. 2006) or entire stream networks (Benstead and Leigh 2002; Jensen et al. 2017; Murphy et al. 2008b) have been field mapped to validate DEM derived stream networks. However, Jensen et al. (2017) determined that it requires a full day to field map the stream network of a 40-45 ha catchment. A research question that remains is therfore; How does one select the correct stream initiation threshold and validate DEM derived stream networks when scaling up from a catchment scale to regional or national scale? Stream initiation thresholds vary between physiographic regions (Avcioglu et al. 2017; Heine et al. 2004) and as the list of National LiDAR datasets is growing (Guo et al. 2017; van Leeuwen and Nieuwenhuis 2010) and high resolution DEMs are becoming accessible to managers it is important to evaluate the performance of these topographically modelled stream networks over larger scales.

The aim of this study was to determine the optimum threshold for stream initiation on a national scale, using the Swedish landscape at a test bench. As to our knowledge, this is the first attempt at working with LiDAR DEM derived stream networks on this large scale. We also asses how accurate these DEM derived stream channels perform in comparison to existing maps of streams and the potential to improve performance of DEM derived stream channel networks by incorporating variability in local topography, soil texture and runoff.

2 Material and methods

2.1 Study site

Sweden is located between latitude 55° and 70° N and longitude 11° and 25° E, placing most of the country within the boreal zone. Annual mean air temperatures range from 8 ˚C in the south to -2 ˚C in the north (Seekell et al. 2014). The bedrock is mainly made up from Precambrian crystalline rocks with remains of younger sedimentary rock in the Caledonian mountains. Sweden has been through multiple glaciations during the last 2-3 million years and most of the quaternary deposits were formed during and after the most recent glaciation, around 10 000 years ago. As a result 75 % of Sweden is covered by glacial till and 13 % is covered by peat (Fransson 2018). The remaining 12 % consists of exposed rock, glaciofluvial and post glacial sedimentary deposits. According to the Swedish Land Cover database (based on satellite imagery) (Ansén 2004) the land cover in Sweden is: Forest 63.0 %, lakes 8.9 %, open mire 8.7 %, heathlands 7.7 %, arable land 6.1 %, forested mire 2.8 %, urban areas 2.3 %, other 0.5 %.

2.2 Field data

As it's not possible to field map all stream channels or stream heads when working on a regional or national scale, we choose to utilise data from the Swedish national inventory of landscapes (NILS) (Ståhl et al. 2011) to evaluate the performance of modelled stream channels. The NILS inventory consists of 631 5*5 km squares, systematically distributed throughout Sweden, covering all landscapes (forest, agricultural areas, mountains, wetlands, shores, and cities). This inventory was designed to secure statistically accurate estimates for the country as a whole and capture variability in rare landscapes. Therefore rare landscapes were sampled with a denser grid while common landscapes were sampled with sparser (Figure 1).

Figure 1: The black points are field sites with observations of stream channels in the NILS database.

Data collected from 631 square shaped line inventories with 200 m line segments, 12 in each square, in total 7 572 segments, giving a total length of the line inventories of 1 512 km was used in this study. 3 323 stream channels narrower than 6 meters were mapped in the line inventory. Instead of mapping stream heads or entire networks, the pixels in the high resolution DEM containing a line inventory can be viewed upon as a point measurement with a presence or absence of a (small <6 m) stream channel, giving a total of 619 767 observations. Due to the national coverage of the field inventory it was impossible to investigate all stream channels during similar flow conditions. Therefore flow conditions during this inventory ranged from "temporarily dried out" to "extreme high flow". Another issue with this dataset was uncertainties in the GPS positioning. Some mapped stream channels were up to 20 m away from its actual location. Especially underneath dense forest canopy. To account for the uncertainties in the GPS positioning the mapped stream channel points were moved, snapped, to the closest modelled stream channel within 20 m.

2.3 Topographically modelled stream channels

The Swedish National DEM generated by the Swedish Mapping, Cadastral and Land Registration Authority using LiDAR data was used for hydrological modelling.

The resolution was 2*2 m and was generated from a point cloud with a point-density of 0.5-1 points /m^2 with a horizontal and vertical error of 0.1 m and 0.3 m, respectively. The mountain region in north-western Sweden were not covered by this DEM at the time of this study. The DEM was split into 2 818 sub catchments where each catchment had 2 km overlap with surrounding catchments to avoid edge effects during stream extraction. The raster stream network grids were later mosaicked back together to form a cohesive stream network before analysis. Before any hydrological calculations could be conducted on the DEM it had to be pre-processed to become hydrologically correct (Marks et al. 1984). Lidberg et al. (2017) showed that breaching was the best way to pre-process high resolution DEMs in the Swedish landscape. Therefore a three step breaching approach was used as described below:

1. Stream lines from the 1:12 500 scale property map, produced by the Swedish Mapping, Cadastral and Land Registration Authority, were burned 1 m into the DEM on agricultural land using the tool "burn streams" in Whitebox GAT 3.4 (Lindsay 2014).
2. Stream lines from the property map were burned across road lines from the property map using the tool "burn streams at roads" in Whitebox GAT 3.4 as described by (Lidberg et al. 2017).
3. Remaining sinks were resolved by the complete breaching algorithm developed by (Lindsay 2015) using Whitebox tools (Lindsay 2018).

A flow accumulation grid was created from the hydrologically correct DEM using deterministic-8 (D8) (O'Callaghan and Mark 1984) and stream channel networks were extracted using stream initiation thresholds of 1 ha, 2 ha, 5 ha, 10 ha, 15 ha and 30 ha. Since the field data only contain channels <6 m, the larger streams were erased using a mask from the Swedish Property map, where all streams >6 m were mapped as a polygon layer. The total lengths of the mosaicked stream channel networks were calculated (Table 1).

2.4 Evaluation of accuracy

As it's not possible to field map all stream channels in Sweden, and we know from experience that the stream networks on current maps (the propery map; 1:12 500) are lacking and therefore cannot be used for validation, field data from the NILS inventory were used to evaluate the performance of the different DEM derived stream networks. The results were evaluated using confusion matrixes, accuracy (ACC) and Mathews Correlation Coefficient (MCC) (Boughorbel et al. 2017). A confusion matrix consist of true positives (TP), i.e. where the map accurately predicts a channel. False positives (FP), i.e. where the map inaccurately predicts a channel. True negatives (TN), where the map accurately predicts the absence of a stream channel and false negatives (FN) where the map misses an existing stream channel (Figure 2). The confusion matrix for the modelled stream channel networks was calculated as follows:

- True positives (TP) were calculated by snapping the coordinates of the field mapped channels to the highest flow accumulation along the inventory line within 20 m. TP, is the number of observations with an accumulated flow above the selected flow initiation thresholds.
- False negatives (FN) were calculated by snapping the coordinates of the field mapped channels to the flow accumulation using a snapping distance of 20 m. FN, is the number of observations with an accumulated flow below the selected flow initiation thresholds.
- False positives (FP) were calculated as number of cells intersecting the line inventories, with a flow initiation above the thresholds, minus the number of TP. A large number of FP's was noted for the modelled stream networks. A common occurrence was that a modelled stream runs along the lines of the field inventory, resulting in several adjacent cells being marked as many FP even though it's just one stream observation. To try and correct for this all adjacent FP's were merged to one observation before calculating the FP. However when a modelled stream is meandering back and forth across the line, it is still considered as several FP.
- True negatives (TN) was calculated as the total number of cells intersecting the line inventories, minus TP, FP and FN. Due to the projection (Sweref 99 TM) the inventory lines are somewhat out of alignment from a straight N-S or W-E line, thereby introducing extra cells (each line should in theory be 1 200 cells, but the lines rage 1 222 to 1 231 cells. This introduces of an overestimation of TN of around 2%, which is negligable for the purpose of this study.

To compare the modeled stream networks with the current best available map the confusion matrix from the Swedish Propery map (1:12 500) was also calulated.

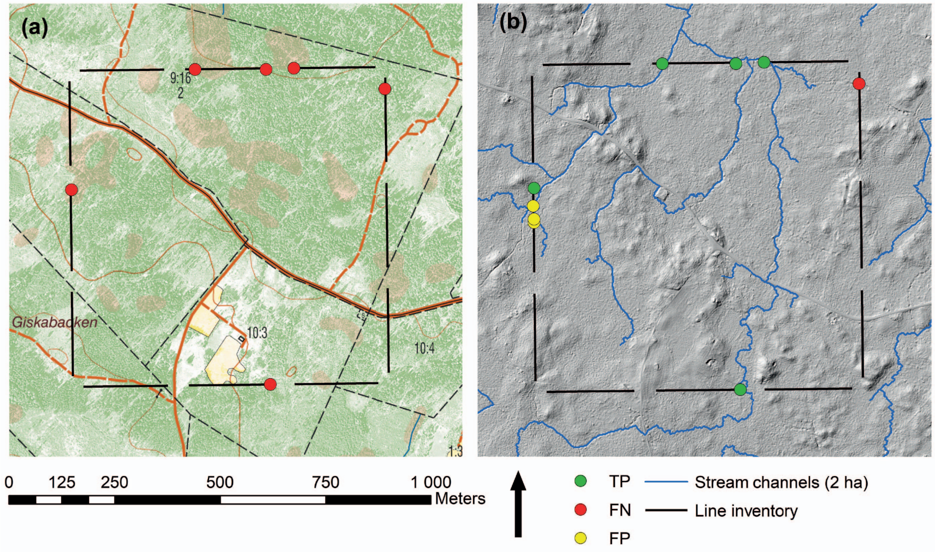

Figure 2. Panel a shows an example of the 200 m segments in the line inventory as black lines superimposed on the Swedish property map (1:12 500) and the red points are field observations of stream channels, in this case all streams were missing on the map (FN). Panel b shows the same square but with a modelled stream channel network (2 ha) superimposed on a hillshade. The green points indicate streams that are accurately shown on the map (TP) while the red points indicate streams that are still missing on the map (FN).Yellow points are locations where the modelled stream channel network intersect an inventoried line without an observation of a stream channel (FP). To summarize the results in panel B; the 2 ha stream network captured 5 out of the 6 stream channels, misses one and generates 3 false positives in this case. This illustrates that the new DEM derived stream networks, while not perfect, is an improvement compared to the property map (panel a).

2.4 Residual analysis and potential for improvement

Residuals from the confussion matrix from the optimal stream channel network were converted into an ordinal variable; 1 for FN and 2 for FP to be used to analyse potential improvements of the stream channel network modelling. These residual points were used to extract existing map data as described below. The aim was to understand what caused over estimations (FP) and under estimations (FN) of stream channels.

Variability in runoff from between sites can affect the challelization of water. Annual runoff increases, roughly one order of magnitude, from the SE coast to the NW mountain range. Therefore runoff data provided by the Swedish metrological and hydrological institute was included. A model known as S-HYPE was used to model seasonal runoff in 33605 sub-catchments between 1982 and 2015 (Arheimer et al. 2011). Meteorological seasons of winter, spring, summer and autumn, were used to calculate seasonal as well as annual runoff for each site. Spatial differences in soils can affect permeability and drainage capacity on each site which may impact stream initiation thresholds. Therefore quaternary deposits were extracted from maps created by the Swedish Geological Survey. The scale of these maps ranges from 1:25 000 (1.7 %), 1:50 000 (2.7 %) 1:100 000 (47 %), 1:200 000 (1.4 %), 1:250 000 (21.2 %), 1:750 000 (33.6 %) and 1:1 000 000 (100 %). Some of these maps have significant overlap but and the map with the highest resolution was selected if more than one were avaliable for a site. The quartenary deposits maps were simplified into 5 classes; till, peat, rock outcrops, coarse sediment (e.g. silt to boulders), and fine sediment (e.g. clays). Local topography may also affect the channel initiation (Avcioglu et al. 2017; Imaizumi et al. 2010). Therefore local topography was calculated as a standard deviation of the digital elevation model in a moving window of 5, 10, 20, 40, and 80 cells. High values represent steep terrain and low values flat terrain. The coordinates of each site were also included in the residual analysis in order to capture other potential spatial gradients. First the X-matrix was tested for multicolinearity, using IBM SPSS Statistics 24 and since many of the explanatory variables in the residual analysis showed multicolinearity a multivariate approach was used. In order to enchance group seperation we choose to perform a Orthogonal Projections to Latent Structures Discriminant Analysis (OPLS-DA) using SIMCA 14. Prior to analysis a balanced dataset was created by randomly selecting and equal number of FN and FP and all variables were scaled and centered.

3 Results

The result of the field investigation showed that stream discharge varied with time during the field investigation, 1 % were recorded during extreme high flow, 16 % during high flow, 54 % during normal flow, 11 % during low flow and 18 % channels were temporarily dried out. 33 % were natural channels, 4 % were straightened channels and ditches made up 63 %. Out of the ditches, 15 % were found in agricultural areas, 28 % were roadside ditches, the majority of the rest were found in forested land where 45 % were found in mineral soils and 11 % in peat.

3.1 Confusion matrix

As the flow initiation threshold decreases, the stream network expands and more of the missing headwaters are captured, as indicated by the increasing number of true positives (Table 1, Figure 2). However, simultaneously the number of false positives also increases (Table 1, Figure 2). As an example, out of the 3323 channels in the field inventory, only 618 were found on the property map, while the 1 ha stream channel network located 2185 channels (Table 1). A downside to the new DEM derived 1 ha stream channel network is that it also created a large number of false positives, the number of false positives increased from 143 on the Swedish property map to 5076 for the 1 ha stream network. All stream channel networks have extremely high accuracy at around 99%. However, the numbers for accuracy cannot be trusted due to the imbalance in the data (Daskalaki et al. 2006). This occurs when the sample size in the data classes are unevenly distributed. In our case most of the field sites consist of land and a typical channel intersection only occupy a single cell. For unbalanced datasets, such as this, the best measure of model performance is MCC (Boughorbel et al. 2017; Daskalaki et al. 2006). MCC for the newly derived stream networks from the DEM was highest for the 2 ha flow initiation threshold channel network (0.463).

The length of all streams under <6 m on the property map is 693 042 km which would correspond to a stream initiation threshold of almost 30 ha (Table 1). The 2 ha network which was the most accurate was 4.5 times longer (2 639 163 km) than the stream channel network currently on the property map.

Table 1. *Confusion matrix showing true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN), as well as accuracy (ACC (%)), Mathews Correlation Coefficient (MCC) and stream length for stream channel networks with different f.i.t (flow initiation thresholds) which is the catchment area required to form a channel.*

Mapped stream channels	TP	TN	FP	FN	ACC (%)	MCC	Length (km)
Channel network with 1 ha f.i.t	2 185	611 575	5 076	931	99.0	0.456	3 811 247
Channel network with 2 ha f.i.t	1 869	613 360	3 291	1 247	99.3	0.463	2 639 163
Channel network with 5 ha f.i.t	1 429	614 845	1 806	1 687	99.4	0.447	1 603 704
Channel network with 10 ha f.i.t	1 107	615 513	1 138	2 009	99.5	0.416	1 089 122
Channel network with 15 ha f.i.t	914	615 793	858	2 202	99.5	0.387	864 370
Channel network with 30 ha f.i.t	684	616 103	548	2 432	99.5	0.347	576 452
Property map stream lines	618	616 301	143	2 705	99.5	0.387	593 042

3.2 Residual analysis

In an ideal world, the two classes (FP and FN) would have separated on either side of the score scatter plot (Fig. 3A), however, the scores showed a large overlap between the two groups; FP and FN. The predictive power of the model was also quite low with R2Y(cum) = 0.16 and R2X(cum) = 0.59 and Q2(cum) = 0.15, meaning that only 15 % of the variability in the X-variables was correlated to the two classes. However, despite low predictive power, we can still analyse the loading plot to detect in what landscapes FP and FN are over-represented.

According to the loading scatter plot (Fig. 3B) more FN are found in regions with high runoff during winter and in areas with high standard deviation (i.e. in steep terrain). More FP's are found in regions with high Y and X-coordinates, where summer and spring runoff is high. When looking at quaternary deposits FNs were mostly found on fine sediments while FPs were found on peat and till.

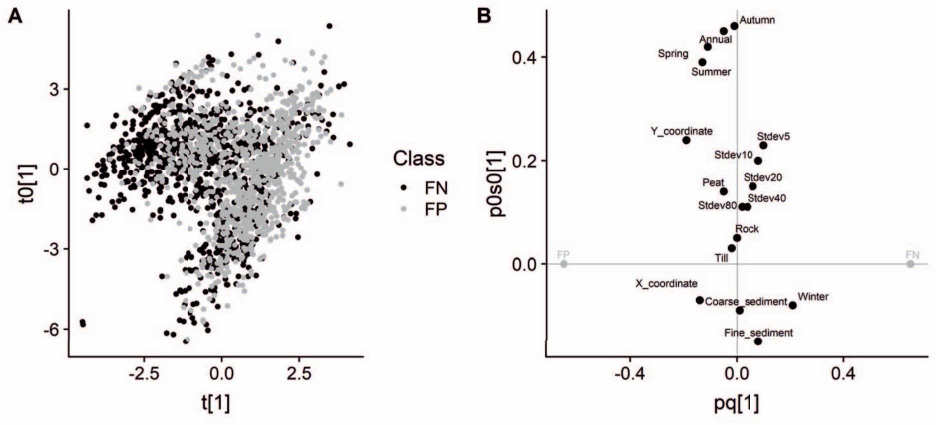

Figure 3. A Score scatter plot from the OPLS-DA model. B) Loading scatter plot from the OPLS-DA model. The variables "Winter, Spring, Summer, Autumn and Annual" refers to the seasonal and annual runoff.

4 Discussion

A striking result of this study was that 81.5 % of the NILS field mapped channels were missing on the Swedish property map (Table 1). Similar result were found in a detailed study of the 68 km^2 Krycklan Catchment in Northern Sweden, where the stream network on current maps were missing 58 % of the perennial and 76 % of the fully expanded network during high flow (Ågren et al. 2015). MCC (Table 1) suggest that a modelled stream channel network with a flow initiation threshold of 2 ha is the most accurate stream network for the Swedish landscape, and therefore an improvement compared to the property map. However, a downside to the new DEM derived 2 ha stream channel network is that it also created a large number of false positives, the number of false positives increased from 143 on the property map to 3291 for the 2 ha stream channel network.

The relatively low optimal channel initiation threshold of 2 ha in this study can be explained by relatively humid climate and high hydraulic conductivity of the Fennoscandia till soils but also extensive human impacts on drainage systems. It's close to the 1.7 ha average channel initiation threshold found in Kansans (Heine et al. 2004). 63 % of all field mapped channels in this study were man made ditches, 4 % were straightened channels (for timer floating) and only 33 % were natural channels. Ditches have been dug for different purposes, for example; to increase rational agricultural production (Avilés et al. 2018), to increase timber production on wet forest soils or mires (Lõhmus et al. 2015) or to stabilize roads (Kalantari and Folkeson 2013). Similar numbers were found in a study on the ditch network in the Krycklan Catchment in Northern Sweden, which showed that the ditch network doubled the length of the stream channel network (Hasselquist et al. 2017). This is due to a long a history of ditching in the Nordic countries that stared in the late 1800s or early 1900 (Hasselquist et al. 2017). This practice has fundamentally changed the hydrology of the landscape where many patches of wet soils with subsurface flow have been ditched, draining the land, lowering the water table and creating many more channels in the landscape. Without these man-made channels the optimum flow initiation for the Swedish landscape would likely be higher. When applying the same methodology to other landscapes and biomes it's therefore necessary to adapt the models and find the optimum flow initiation threshold for that landscape.

There is a considerable seasonal variability in the stream networks. This variability in the stream networks were for example seen in the field inventory where 18 % were recorded as temporarily dried out at the time of the investigation. A detailed study conducted in the Krycklan Catchment, Northern Sweden where the position of stream heads were field mapped during different times of the year showed that the natural stream heads were normally found at a threshold of around 10-15 ha during baseflow and expanded to 2 ha in natural streams during high-flow conditions and up to as low as 1 ha for ditches (Ågren et al. 2015). How large this inter-annual variability is largely depend on soils and climate of the site. Still, the study in the Krycklan Catchment gives conservative estimate that the length of the stream network at high-flow conditions is 2.4 times the length at baseflow conditions. Similar results was found by

(Jensen et al. 2017) in the Appalachia Mountains. The length of the stream network on the property map was of the same order as the 30 ha stream network (Table 1), which would correspond to the stream network during extreme dry conditions. While this constitutes a perennial stream network it's important to realize that perennial stream networks are extreme cases and not very representative of "normal" or "average" stream networks in a landscape.

In this study a fixed threshold for the channel heads were chosen. This will introduce a bias, not only because of the seasonal variability, but also because the upslope areas of channel heads vary between different physiographic regions. Avcioglu et al. (2017) report that the upslope areas for channel heads range 0.03-7.6 ha in 3 physiographic regions in Alabama and Jensen et al. (2017) report correpsonding numbers of 0.3-3.9 ha in 4 physiographic regions of the Appalchian Highlands. There are other methods to determine position of channel heads in watersheds, that are based on finding thresholds where water has enough energy to start eroding soil and form a channel head, for example the slope-area method which develop slope-area threshold relationships from the DEM, (Avcioglu et al. 2017; Imaizumi et al. 2010; Heine et al. 2004) or logistic regression (Heine et al. 2004). Such methods perform better in steeper terrain and poorer in flat terrain (McNamara et al. 2006). However, such algorithms depend on the natural formation of channel heads. In Sweden and other heavily drained countries, such as Finland and the Baltic States (Lõhmus et al. 2015) this has been offset by human influence and the numerous man-made channels draining the landscape. Also, based on the field data being point data of stream presence/absence and not actual channel heads it's not possible to use these methods. Instead the bias introduced by choosing a fixed threshold was investigated via a residual analysis.

The residual analysis (Figure. 3) show that there is a potential to further improve the channel networks by considering spatial variability, but the OPLS-DA could only explain 15% of overestimation and underestimation of stream channels (FPs and FNs). For example, more FNs were found in the south west while FPs were found in the eastern and northern regions. While the coordinates themselves are not exerting controls on the channel head initiation, they capture many spatial gradients such as elevation, climate and even land use. Southern Sweden is characterized by an agricultural landscape while northern Sweden is mostly covered in forest. More FNs were found in south-western regions with high runoff during winter and on sedimentary soils which could be a result of agricultural drainage that contributes to more stream channels. FP on the other hand were mostly found in drier regions towards the east where summer and spring runoff is lower as well as in northern Sweden. It's difficult to interpret these results since it's likely that both anthropogenic drainage systems for agriculture and forestry overlaps with quaternary deposits and topography. Additionally it's important not to read too much into these results since the residuals showed extensive overlap and the model had low predictive power.

Despite difficulties in modelling something so variable in space and time as small streams, the 2 ha stream channel network, while far from perfect, is still an improvement compared to the stream network on the property map (MCC increased from 0.39 to 0.46 (Table 1)), and therefore has many applications as a management tool. The 2 ha stream network can be used in forestry (Murphy et al. 2008a, 2008b) landscape planning and as best management practice as suggested by (Kuglerová et al. 2017). In forestry it can be used to, for example, plan off road driving (Ågren et al. 2015; Mohtashami et al. 2017) or design machine free zones on sensitive soils in riparian areas along the channels (Kuglerová et al. 2014). Thereby preventing increasing loads of sediment or mercury to surface waters (Kreutzweiser and Capell 2001). An important improvement compared to the property map is that it not only captures more headwater streams, the channels also follows the inundated channel in the DEM (Murphy et al. 2008a), placing the streams more correctly while streams on the property maps are lines drawn approximately where the streams are. These new derived stream channel networks also form an integrated drainage network where the amount of water to each stream section can be calculated. During road construction this can be used to correctly place and dimension culverts, which can decrease the problem with roads washing out during flood events (Prasad et al. 2005). When such an event happens its costly not only for the land/road owner, it also comes at a cost for the downstream environments that receives increasing loads of sediment transport (Najafi and Bhattachar 2011). Another benefit of the connectivity in the newly mapped streams, reflecting the connectivity of water, is that effects can be traced upstream or downstream. For example, any effect of a perturbation in the stream network at an upstream location (road construction, ditch cleaning, soil erosion, clear-cuts, ruts, etc.) can now be traced downstream. This can form an important planning tool in order to protect streams of high ecological status at a downstream site, as the quality there is not only reflecting the management of the downstream site but also the sum of all upstream management.

Another important use for the 2 ha stream network is for upscaling from process based studies to large scale budgets on any scale. Streams and rivers dominate the carbon dioxide emissions of inland waters and low order streams are suggested to be disproportional contributors emitting more than 70 % of the total stream and river CO2 (Raymond et al. 2013). Wallin et al. (2018) calculated the evasion from streams in Sweden and estimated a total loss of CO2 to 2.7 Tg C yr^{-1} and CH4 to 0.02 Tg C yr^{-1}. These numbers were derived from a 400,000 km stream network based on a 50 m x 50 m DEM. This stream length would correspond to >30 ha stream channel initiation threshold while the 2 ha network had a length of 2 639 163 km or 6.6 times longer. Clearly, this indicates that the CO2 and CH4 evasion, during most part of the year apart from extreme dry situations in Sweden is even larger that the suggested numbers from Wallin et al. (2018). This illustrates how important accurate stream networks are for both management and upscaling aquatic and climate research and constrain C emissions.

5 Conclusions

The majority of the smaller (<6 m width) stream channels in this study were missing on the Swedish property map. A more accurate stream network map has many uses in landscape planning and best management practice. Also, incorrect representations of stream networks, up to many times over, severely affect upscaling aquatic and climate research, a problem that increases with scale. This study clearly show that a solution to this is to map stream channel networks from high resolution digital elevation models. For the study region of Sweden, which was used as a test bench, a 2 ha flow initiation threshold yielded the optimum stream network, increasing MCC from 0.387 on the property map to 0.463. When applying the same methodology to other biomes it's necessary to adapt the models and find the optimum flow initiation threshold for that unique landscape.

6 Acknowledgements

This project was financed by the EU InterReg Baltic Sea project WAMBAF, VINNOVA, Mistra - Future Forests, Formas - ForWater, and the Kempe foundation. Finally, we thank the National Inventory of Swedish Landscapes for providing the field reference plots.

References

Ågren, M. A., Lidberg, W., and Ring, E.: Mapping Temporal Dynamics in a Forest Stream Network—Implications for Riparian Forest Management. *Forests*, 6, 2982–3001, https://doi.org/10.3390/f6092982, 2015.

Ansén, H.: Marktäckedata 2000. Official Statistics of Sweden, MI 67 SM 0401, Umeå, Sweden, 2004.

Arheimer, B., Dahné, J., Lindström, G., Marklund, L., and Strömqvist, J.: Multi-variable evaluation of an integrated model system covering Sweden (S-HYPE). *IAHS Publ*., 345, 145–150, 2011.

Avcioglu, B., Anderson, C. J., and Kalin, L.: Evaluating the Slope-Area Method to Accurately Identify Stream Channel Heads in Three Physiographic Regions. J. Am. *Water Resour. Assoc*., 53, 562–575, https://doi.org/10.1111/1752-1688.12512, 2017.

Avilés, D., Wesström, I., and Joel, A.: Status assessment of agricultural drainage ditches. *Trans. ASABE*, 61, 263-271, https://doi.org/10.13031/trans.12307, 2018.

Benstead, J. P., and Leigh, D. S.; An expanded role for river networks. *Nat. Geosci*., 5, 678–679 https://doi.org/10.1038/ngeo1593, 2012.

Bishop, K., Buffam, I., Erlandsson, M., Fölster, J., Laudon, H., Seibert, J., and Temnerud, J.: Aqua Incognita: the unknown headwaters. *Hydrol. Process*., 22, 1239–1242, https://doi.org/10.1002/hyp.7049, 2008.

Blackburn, M., Ledesma, J. L. J., Näsholm, T., Laudon, H., and Sponseller, R. A.: Evaluating hillslope and riparian contributions to dissolved nitrogen (N) export from a boreal forest catchment. *J. Geophys. Res. Biogeosci*., 122, 324–339, https://doi.org/10.1002/2016JG003535, 2017.

Bormann, F. H., and Likens, G. E.: Nutrient cycling. *Science*, 80, 155, 424–429, https://doi.org/10.1126/science.155.3761.424, 1967.

Boughorbel, S., Jarray, F., and El-Anbari, M.: Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. *PLoS One,* 12, https://doi.org/10.1371/journal.pone.0177678, 2017.

Daskalaki, S., Kopanas, I., and Avouris, N.: Evaluation of classifiers for an uneven class distribution problem. *Appl. Artif. Intell*., 20, 381-417, https://doi.org/10.1080/08839510500313653, 2006.

Fransson, J., 2018. Skogsdata 2018. Official Statistics of Sweden, Swedish University of Agricultural Sciences, Umeå, Sweden, Infra service SLU, Uppsala, Sweden, 148 pp, 2018.

Freeman, M. C., Pringle, C. M., and Jackson, C.R.: Hydrologic connectivity and the contribution of stream headwaters to ecological integrity at regional scales. *J. Am. Water Resour. Assoc*., 43, 5–14, https://doi.org/10.1111/j.1752-1688.2007.00002.x, 2007.

Gonzalez-Ferreras, A, M., and Barquin, J. Mapping the temporary and perennial character of whole river networks. *Water Resour. Res.,* 53, 6709-6724, https://doi.org/10.1002/2017WR020390, 2017.

Goulden, T., Hopkinson, C., Jamieson, R., and Sterling, S.: Sensitivity of watershed attributes to spatial resolution and interpolation method of LiDAR DEMs in three distinct landscapes. *Water Resour. Res*., 50, 1908–1927, https://doi.org/10.1002/2013WR013846, 2014.

Guo, M., Li, J., Sheng, C., Xu, J., and Wu, L.: A review of wetland remote sensing. *Sensors*, 17, https://doi.org/10.3390/s17040777, 2017.

Hasselquist, E. M, Lidberg, W., Sponseller, R. A., Ågren, A., and Laudon, H.: Identifying and assessing the potential hydrological function of past artificial forest drainage. *Ambio*, 47, 1–11, https://doi.org/10.1007/s13280-017-0984-9, 2017.

Heine, R. A., Lant C. L., and Sengupta, R. R.: Development and Comparison of Approaches for Automated Mapping of Stream Channel Networks, Ann. *Assoc. Am. Geogr*., 94, 477-490, https://doi.org /10.1111/ j.1467-8306.2004.00409.x, 2004.

Imaizumi, F., Hattanji, T., and Hayakawa, Y. S.: Channel initiation by surface and subsurface flows in a steep catchment of the Akaishi Mountains, Japan. *Geomorphology*, 115, 32–42, https://doi.org/10.1016/j.geomorph.2009.09.026, 2010.

Jaeger, K. L., Sando, R., McShane, R, R., Dunham, J B., Hockman-Wert, D, P., Kaiser, K, E. and Hafen, K. Probability of Streamflow Permanence Model (PROSPER): A spatially continuous model of annual streamflow permanence throughout the Pacific Northwest. *J Hydrology*., 2, https://doi.org/10.1016/j.hydroa.2018.100005, 2019.

Jensen, C. K., McGuire, K. J., and Prince, P. S.: Headwater stream length dynamics across four physiographic provinces of the Appalachian Highlands. *Hydrol. Process*., 31, 3350–3363, https://doi.org/10.1002/hyp.11259, 2017.

Julian, J, P., Elmore, A, J., and Guinn, S, M.: Channel Head Locations in Forested Watersheds across the Mid-Atlantic United States: A Physiographic Analysis. *Geomorphology*., 1, 194-203, https://doi.org/10.1016/j.geomorph.2012.07.029, 2012.

Kalantari, Z., and Folkeson, L.: Road Drainage in Sweden: Current Practice and Suggestions for Adaptation to Climate Change. *J. Infrastruct. Syst*., 19, 147–156, https://doi.org/10.1061/(ASCE)IS.1943-555X.0000119, 2013.

Klaminder, J., Bindler, R., Laudon, H., Bishop, K., Emteryd, O., and Renberg, I.: Flux rates of atmospheric lead pollution within soils of a small catchment in Northern Sweden and their implications for future stream water quality. *Environ. Sci. Technol*., 40, 4639–4645, https://doi.org/10.1021/es0520666, 2006.

Kreutzweiser, D. P., and Capell, S. S.: Fine sediment deposition in streams after selective forest harvesting without riparian buffers. Can. *J. For. Res*., 31, 2134–2142, https://doi.org/10.1139/x02-086, 2001.

Kuglerová, L., Ågren, A., Jansson, R., and Laudon, H.: Towards optimizing riparian buffer zones: Ecological and biogeochemical implications for forest management. *For. Ecol. Manage*., 334, 74–84, https://doi.org/http://dx.doi.org/10.1016/j.foreco.2014.08.033, 2014.

Kuglerová, L., Hasselquist, E. M., Richardson, J. S., Sponseller, R. A., Kreutzweiser, D. P., and Laudon, H.: Management perspectives on Aqua incognita: Connectivity and cumulative effects of small natural and artificial streams in boreal forests. *Hydrol. Process*., 31, 4238–4244, https://doi.org/10.1002/hyp.11281, 2017.

Laudon, H., Taberman, I., Ågren, A., Futter, M., Ottosson-Löfvenius, M., and Bishop, K.: The Krycklan Catchment Study - A flagship infrastructure for hydrology, biogeochemistry, and climate research in the boreal landscape. *Water Resour. Res*., 49, 7154–7158, https://doi.org/10.1002/wrcr.20520, 2013.

Leach, J. A. A., Lidberg, W., Kuglerová, L., Peralta-Tapia, A., Ågren, A., and Laudon, H.: Evaluating topography-based predictions of shallow lateral groundwater discharge zones for a boreal lake-stream system. *Water Resour. Res*., 53, 5420–5437, https://doi.org/10.1002/2016WR019804, 2017.

Lidberg, W., Nilsson, M., Lundmark, T., and Ågren, A. M.: Evaluating preprocessing methods of digital elevation models for hydrological modelling. *Hydrol. Process*., 31, 4660–4668, https://doi.org/10.1002/hyp.11385, 2017.

Lidman, F., Boily, Å., Laudon, H., and Köhler, S. J.: From soil water to surface water-how the riparian zone controls element transport from a boreal forest to a stream. *Biogeosci*., 14, 3001–3014, https://doi.org/10.5194/bg-14-3001-2017, 2017.

Lindsay, J.B., 2014. The Whitebox geospatial analysis tools project and open-access GIS. Proceedings of the GIS Research UK 22nd Annual Conference, The University of Glasgow, UK., 16–18 April. 1–8, https://doi.org/10.13140/RG.2.1.1010.8962, 2014.

Lindsay, J. B.: Efficient hybrid breaching-filling sink removal methods for flow path enforcement in digital elevation models. *Hydrol. Process*., 21, 846-857, DOI: https://doi.org/10.1002/hyp.10648, 2015.

Lindsay, J. B.: WhiteboxTools User Manual. Guelph., Canada. https://doi.org/10.13140/RG.2.2.22964.96648, 2018.

Lindsay, J. B., and Creed, I. F.: Removal of artifact depressions from digital elevation models: towards a minimum impact approach. *Hydrol. Process*., 19, 3113–3126, 2005.

Lõhmus, A., Remm, L., and Rannap, R.: Just a Ditch in Forest? Reconsidering Draining in the Context of Sustainable Forest Management. *Bioscience*, 65, 1066–1076, https://doi.org/10.1093/biosci/biv136, 2015.

Marks, D., Dozier, J., and Frew, J.: Automated Basin Delineation from Digital Elevation Data. *Geo-Processing*, 2, 299–311, https://doi.org/10.1016/0165-1684(90)90127-K, 1984.

McNamara, J. P., Ziegler, A. D., Wood, S. H., and Vogler, J. B.: Channel head locations with respect to geomorphologic thresholds derived from a digital elevation model: A case study in northern Thailand. For. *Ecol. Manage*., 224, 147–156, https://doi.org/10.1016/j.foreco.2005.12.014, 2006.

Mohtashami, S., Eliasson, L., Jansson, G., and Sonesson, J.: Influence of soil type, cartographic depth-to-water, road reinforcement and traffic intensity on rut formation in logging operations: A survey study in Sweden. *Silva Fenn*., 51, https://doi.org/10.14214/sf.2018, 2017.

Murphy, P., Ogilvie, J., Castonguay, M., Zhang, C., Meng, F., and Arp, P. A.: Improving forest operations planning through high-resolution flow-channel and wet-areas mapping. For. Chron., 84, 568–574, https://doi.org/10.5558/tfc84568-4, 2008a.

Murphy, P., Ogilvie, J., Meng, F., and Arp, P.: Stream network modelling using lidar and photogrammetric digital elevation models : a comparison and field verification. *Hydrol. Process*., 22, 1747–1754, https://doi.org/10.1002/hyp, 2008b.

Najafi, M., and Bhattachar, D. V.: Development of a culvert inventory and inspection framework for asset management of road structures. J. King Saud Univ. - *Sci*., 23, 243–254, https://doi.org/10.1016/j.jksus.2010.11.001, 2011.

Natchimuthu, S., Wallin, M. B., Klemedtsson, L., and Bastviken, D.: Spatio-temporal patterns of stream methane and carbon dioxide emissions in a hemiboreal catchment in Southwest Sweden. *Sci*. Rep., 7, https://doi.org/10.1038/srep39729, 2017.

O'Callaghan, J. F., and Mark, D. M.: The Extraction of Drainage Networks from Digital Elevation Data. Comput. Vis. Graph. *Image Process*., 28, 323–344, https://doi.org/Doi10.1016/S0734-189x(84)80011-0, 1984.

Prasad, A., Tarboton, D. G., Luce, C. H., and Black, T. A.: A GIS Tool to Analyze Forest Road Sediment Production and Stream Impacts. ESRI Users Conf., San Diego, California, July 25-29, 10 pp, 2005.

Raymond, P. A., Hartmann, J., Lauerwald, R., Sobek, S., McDonald, C., Hoover, M., Butman, D., Striegl, R., Mayorga, E., Humborg, C., Kortelainen, P., Dürr, H., Meybeck, M., Ciais, P., and Guth, P.: Global carbon dioxide emissions from inland waters. *Nature*, 503, 355–359, https://doi.org/10.1038/nature12760, 2013.

Richardson, J. S., and Danehy, R. J.: A synthesis of the ecology of headwater streams and their riparian zones in temperate forests. *For. Sci*., 53, 131-147, https://doi.org/10.1093/forestscience/53.2.131, 2007.

Seekell, D. A., Lapierre, J.-F., Pace, M. L., Gudasz, C., Sobek, S., and Tranvik, L. J.: Regional-scale variation of dissolved organic carbon concentrations in Swedish lakes. *Limnol. Oceanogr.*, 59, 1612–1620, https://doi.org/10.4319/lo.2014.59.5.1612, 2014.

Seibert, J., Grabs, T., Köhler, S., Laudon, H., Winterdahl, M., and Bishop, K.: Linking soil- and stream-water chemistry based on a Riparian Flow-Concentration Integration Model. *Hydrol. Earth Syst. Sci*., 13, 2287–2297, https://doi.org/10.5194/hess-13-2287-2009, 2009.

Ståhl, G., Allard, A., Esseen, P. A., Glimskär, A., Ringvall, A., Svensson, J., Sundquist, S., Christensen, P., Torell, Å. G., Högström, M., Lagerqvist, K., Marklund, L., Nilsson, B., and Inghe, O.: National Inventory of Landscapes in Sweden (NILS)-scope, design, and experiences from establishing a multiscale biodiversity monitoring system. *Environ. Monit. Assess*., 173, 579–595, https://doi.org/10.1007/s10661-010-1406-7, 2011.

Tiwari, T., Lidman, F., Laudon, H., Lidberg, W., and Ågren, A. M.: GIS-based prediction of stream chemistry using landscape composition, wet areas, and hydrological flow pathways. J. Geophys. Res. *Biogeosci.*, 122, 65-79, https://doi.org/10.1002/2016JG003399, 2017.

van Leeuwen, M., and Nieuwenhuis, M.: Retrieval of forest structural parameters using LiDAR remote sensing. Eur. J. *For. Res*., 129, 749-770, https://doi.org/10.1007/s10342-010-0381-4, 2010.

Vaze, J., and Teng, J.: Impact of DEM Resolution on Topographic Indices and Hydrological Modelling Results. Proceedings of MODSIM07 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, 706–712, 2007.

Wallin, M., Campeau, A., Audet, J., Bastviken, D., Bishop, K., Kokic, J., Laudon, H., Lundin, E., Löfgren, S., Natchimuthu, S., Sobek, S., Teutschbein, C., Weyhenmeyer, G. A., and Grabs, T.: Carbon dioxide and methane emissions of Swedish low-order streams-a national estimate and lessons learnt from more than a decade of observations. *Limnol. Oceanogr. Lett*., 3, https://doi.org/10.1002/lol2.10061, 2018.

Wallin, M., Grabs, T., Buffam, I., Laudon, H., Ågren, A., Öquist, M. G., and Bishop, K.: Evasion of CO2 from streams - the dominant component of the carbon export through the aquatic conduit in a boreal landscape. *Glob. Chang. Biol*., 19, 785–97, https://doi.org/10.1111/gcb.12083, 2013.

Wipfli, M.S., Richardson, J.S., and Naiman, R. J., Ecological linkages between headwaters and downstream ecosystems: Transport of organic matter, invertebrates, and wood down headwater channels. J. Am. *Water Resour. Assoc*., 43, 72–85. https://doi.org/10.1111/j.1752-1688.2007.00007.x, 2007.

III

Using machine learning to generate high resolution wet area maps for planning forest management. A study in a boreal forest landscape.

William Lidberg[1], Mats Nilsson[2] and Anneli M. Ågren[1]

[1] Department of Forest Ecology and Management, Swedish University of Agricultural Sciences, Umeå, Sweden.

[2] Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden.

Manuscript

Abstract

Comparisons between field data and available maps of wet areas show that 64 % of wet areas in the boreal landscape are missing on current maps. Primarily forested wetlands and wet soils near streams and lakes are missing, making them difficult to manage. One solution is to model missing wet areas from high resolution digital elevation models, using indices such as topographical wetness index and depth to water. However, when studying large areas working across large gradients in topography, soils and climate, it is not possible to find one method or one threshold that works everywhere. By using soil moisture data from the National Forest Inventory of Sweden as a training dataset, we show that it's possible to combine information from several indices and thresholds, using machine learners, thereby improving the mapping of wet soils (kappa=0.65). The new maps can be used to better plan roads and generate riparian protection zones near surface waters.

Keywords: Digital elevation model; Machine learning; LiDAR; Random Forest; Soil classification; Wet area mapping

1 Introduction

Open peatlands are a recognisable feature in the boreal landscape that are commonly mapped from aerial photographs. However wet soils occur on tree covered peatlands (Creed et al. 2003), the riparian zones of forest streams and surrounding lakes (Gregory et al. 1991). Wet soils have lower bearing capacity than dry soils (Cambi et al. 2015) and are more susceptible to soil disturbance from land use management with heavy machinery (Mohtashami et al. 2017). Off road driving with heavy machines can cause wet soils to deform and displace resulting in deeper tracks and larger soil disturbance than on dry soils where shallower tracks are caused by compation. Forestry conducted in close connectivity with streams and lakes, have been shown to increase the export of mercury (Eklöf et al. 2016) and nutrients (Kreutzweiser et al. 2008) to downstream environments (Kuglerová et al. 2014). Soil damage in riparian zones can also lead to erosion from ruts and subsequent sediment deposition burying important spawning habitats (Kreutzweiser and Capell 2001). Forested buffer zones and machine free areas near streams and lakes are commonly used to protect surface water during forestry activities but implementing these protective measures can be complicated due to poor planning tools. For example, Ågren et al. (2015) compared manually mapped streams to current maps and concluded that 60 % of the perennial stream network and 80 % of all streams are missing from current maps in Sweden. This makes it difficult for managers to plan off road driving and protective measures, particularly buffer zones around streams (Laudon et al. 2016; Kuglerová et al. 2017).

Topographical modelling of wet area indices has been suggested as a solution to this problem (Murphy et al. 2008) and high resolution digital elevation models (DEM) derived from Light Detection And Ranging (LiDAR) are becoming accessible in many countries, making this a popular approach (van Leeuwen and Nieuwenhuis 2010; Guo et al. 2017). Topographic wetness index (TWI) (Beven and Kirkby 1979) is often used to map wet areas but is sensitive to DEM resolution (Ågren et al. 2014) as well as which algorithms is used to calculate TWI (Sørensen et al. 2006). Creed and Beall (2009) later built on TWI with variable source area (VSA) to map cryptic wetlands and predict nitrogen transport to streams in Canada. Hjerdt et al. (2004) suggested downslope distance or downslope gradient index but this method requires catchment specific thresholds to define wet areas. Wet area indices based on stream networks, such as elevation above stream (EAS) (Rennó et al. 2008) and cartographic depth to water (DTW) (Murphy et al. 2008), have already proven to be useful and DTW maps are used today in for example Sweden and Canada to plan forestry operations. However since they are based on stream networks it is necessary to define a stream initiation threshold. Something that has proven to be difficult due to temporal dynamics

(Ågren et al. 2015) and spatial distribution of soils types (Ågren et al. 2014). An early attempt to include soil transmissivity in TWI was done by Beven (1986) and more recent attempts include both soil and climate (Güntner et al. 2004). Most of these topographical methods rely on the user to define appropriate threshold values in order to define wet areas. Ågren et al. (2014) demonstrated that the optimal flow initiation threshold used to extract depth to water maps (DTW) varied greatly even on a local scale. Soil textures, topography and climatic differences make any application on a large scale difficult. To handle these limitations new methods are necessary. Such new methods include the use of machine learning (ML) in digital soil mapping (Maxwell et al. 2018). ML is a data mining technique that finds patterns in datasets and uses these patterns to predict new data. Several ML algorithms are available (Hastie et al. 2009) but the optimal method depends on the nature of the problem and it's usually recommended to explore several algorithms (Maxwell et al. 2018).

The aim of this study is to evaluate if ML and national inventories data can be used with wet area indices and existing map data to generate more accurate maps of wet soils on a high resolution that can be used to plan forestry operations.

2 Materials and Methods

2.1 Study Site

Sweden is situated in Northern Europe between latitude 55° and 70° N and longitude 11° and 25° E, which means that most of the country is within the boreal zone. Sweden is to 75% covered by glacial till while peat is the second most dominant soil type and covers 13 % of Sweden (Fransson 2018). According to the Swedish Land Cover database (based on satellite imagery) (Ansén 2004) the land cover in Sweden is; Forest 63.0%, lakes 8.9%, open mire 8.7%, heathlands 7.7%, arable land 6.1%, forested mire 2.8%, urban areas 2.3%, and other 0.6%. However the NFI estimates that 67 % of Sweden is forest land (Fransson 2018).

2.2 Field Data

The Swedish National Forest Inventory (NFI) started in 1923. It contains both permanent plots with a radius of 10 m and temporal plots with a radius of 7 m. Permanent plots inventoried between 2012 and 2016 were used for this study due to better accuracy in GPS positioning than temporal plots. The accuracy of these plots was within 5 - 10 m. The NFI includes a random sampling of both productive forestland (defined as areas with a potential yield capacity of >1 m^3 mean annual increment per ha) and low-productive forest land (potential yield capacity of <1 m^3 mean annual increment per ha) for example; peatlands, pastures, thin soils, rock outcrops and areas close to and above the tree-line. However, crop fields, urban areas, roads, railroads, and power lines are excluded from the random sampling. This means that the registrations of soil moisture gives a good representation of the distribution of soil moisture in the landscape outside of urban and arable areas. Further, only sites covered by the Swedish National DEM could be included in this study resulting in 19 645 plots (Figure 1). These plots where used as training data for the machine learning classification described in the classification section below.

The NFI registers average soil moisture condition in each plot based on vegetation patterns and the position in the landscape in five classes: Dry (6 %), mesic (54 %), mesic–moist (27 %), moist (10 %) and wet (3 %) (out of the sample plots on productive and non-productive forest land). Estimating soil moisture from vegetation is a way to ignore temporal variations and instead determine the general wetness regime. Here follows a short description on each soil class:

- Wet soil are soils normally open peatlands classified as bogs or fens, trees can occasionally occur but not in dense stands. The groundwater table is close to the soil surface and permanent ponds are common, soils are histosols or gleysols. The thickness of the organic layer is often >30 cm. One cannot walk dry footed on wet soils and it's often not possible to cross wet soils with heavy machinery unless soils are frozen during winter.

- Moist soils are areas with a shallow groundwater level (<1 m). Pools of standing water are visible in local pits. It's possible to cross these areas dry footed in low shoes if you utilise higher lying areas and tussocks, however, a pool of water should form around the shoe in lower laying areas, even after dryspells. Soils are histosols or gleysols, they can also be categorized as regosols which is a taxonomic rest group. Vegetation is dominated by wetland mosses (e.g. *Sphagnum sp., Polytrichum commune, Polytrichastrum formosum, Polytrichastrum longisetum*) and (*Sphagnum sp.*) dominates local depressions. Trees show a course root system above ground and tussocks are common indicating an adaption to high groundwater levels in these areas, The thickness of the organic layer is not used to define moist areas but it is often >30 cm.

- Mesic-moist soils are areas where the groundwater table is on average less than 1 m from the soil surface. Normally flat areas on lower laying grounds or on lower parts of hillslopes. These soils wet up on a seasonal basis following snowmelt or rain. If you can cross these areas dry footed or not depend on the season. Wetland mosses (e.g. *Sphagnum sp., Polytrichum commune, Polytrichastrum formosum, Polytrichastrum longisetum*) are common and trees show a course root system above ground indicating that high groundwater levels are common in these areas. Soils are humo-ferric to humus-podsols. The organic soils are thicker than on mesic soils and while podsols are common the O-horizon is still often peaty (peaty moor).

- Mesic soils consists of ferric podsols with a thin humus layer covered by mainly dry land mosses (e.g. *Pleurozium schreberi, Hylocomium splendens, Dicranum scoparium*). The groundwater table is on average 1- 2 m below the soil surface. Here you can walk dry footed even directly after rain or shortly after snowmelt. The organic layers are normally 4-10 cm.

- Dry soils have the groundwater table at least 2 m below the surface, course textured and found on hills, eskers, ridges and marked crowns. Soils are leptosols, arenosols, regosols or podzols (the podzols have thin organic and bleached soil horizons).

Figure 1. The 19 645 NFI field plots are marked with black points. The density of field plots are higher in southern Sweden than northern Sweden and the white regions in north western Sweden were not yet scanned with LiDAR at the time of this study.

Here we focus on a forest management perspective, where the main aim is to generate a map for forest soil trafficking. Wet soils are too wet to drive on unless frozen or using technical aids. While it is possible to cross moist soils and mesic-moist soils with heavy machinery, it's best to avoid them since they have a relatively low bearing capacity. The high wetness and high organic content of moist soils and mesic-moist soils makes them deform and displace easily, causing more soil disturbance and deeper rut formation compared to the dryer more minerogenic dry and mesic soils where the tracks are shallower and normally only formed due to compaction of soils (Williamson et al. 2000). Consequently, we divided the NFI dataset into two categories, "wet" and "dry". Dry and mesic plots were classified in the "dry" category (60 % of the NFI plots) while mesic-moist, moist and wet plots were classified in the "wet" category (40% of the NFI plots). This means that the "wet" category contains more mesic-moist plots than actual wet plots. Mesic-moist soils is not normally associated with open peatlands or wetlands but the definition of soils < 1 m depth to the groundwater table as unsuitable for trafficking also agrees with previous wet area mapping to define wet soils (Murphy et al. 2008; Ågren *et al.*, 2014). We argue that "wet" soils are more sensitive to runt formation and it's better to traffic "dry" soils. To avoid confusion we write wet when we mean a more general description of wet conditions, and "wet" when we refer to new binary "wet"/"dry" grouping described above, this agrees with the terminology used in previous studies on wet area mapping (Murphy et al. 2008; Ågren et al. 2014), however "wet" soils are not necessarily wet, *per se*.

2.3 Variables Derived from the Digital Elevation Model

To locate "wet" soils several terrain indices were calculated that predict the location of "wet" soils based on the assumption that topography controls the groundwater flow. This study used the Swedish National DEM generated by the Swedish Mapping, Cadastral and Land Registration Authority using LiDAR data. This DEM has a cell resolution of 2 m * 2 m and was generated from a point cloud with a point-density of 0.5 - 1 points m^{-2} with a horizontal and vertical error of 0.1 m and 0.3 m, respectively. The DEM was split into 2 818 sub catchments where each catchment had 2 km overlap with surrounding catchments to avoid edge effects when extracting streams. These sub catchments were processed separately for topography (section 2.3.1), elevation above stream (section 2.3.3) and depth to water (section 2.3.4) and the outputs were mosaicked back together before the values were extracted to the field plots. All input layers and their utilized scales, thresholds and periods are summarized in table 1.

Table 1. *The table summarizes the GIS layers used to model the distribution of "wet" and "dry" soils with machine learners. Previous wet area maps used in forest management often consisted of just one method and threshold (DTW 1 or 2 ha stream initiation threshold has been a common approach, but other methods have also existed). By combining several terrain indices, thresholds and variability in runoff and using a training data set (NFI) that captures the distribution of "wet" soils on productive and non-productive forest lands all over the country, it's possible to generate an optimal "wet" area map across gradients in soil textures, topography and climate. This is necessary when scaling up from a catchment scale to a national scale.*

In-data map layers used to classify "wet" and "dry" area with machine learners	Utilized scales, thresholds and periods	Source
Local topography	Moving window with 5*5, 10*10, 20*20, 40*40 and 80*80 grid cells	Calculated from the national 2 m DEM
Elevation Above Stream	Stream initiation thresholds of 0.5 ha, 1 ha, 2 ha, 5 ha, 10 ha, 15 ha and 30 ha	Calculated from the national 2 m DEM
Depth to Water	Stream initiation thresholds of 0.5 ha, 1 ha, 2 ha, 5 ha, 10 ha, 15 ha and 30 ha	Calculated from the national 2 m DEM
Topographic Wetness Index	Resampled to a 24 m DEM and a 48 m DEM	Calculated from 24 & 48 m DEM
Quaternary deposits		From Swedish Geological Survey
Wetlands from the 1:12 500 scale property map		From Swedish Mapping, Cadastral and Land Registration Authority
Runoff	Spring, summer, autumn, winter and annual average runoff	Calculated with S-HYPE (Arheimer *et al.* 2011)

2.3.1 Local Topography

Local topography is recognized as an important factor for controlling soil moisture (Moeslund et al. 2013) and one way to extract values of local topography is to use the standard deviation elevation from a DEM. Here a moving window with 5*5, 10*10, 20*20, 40*40 and 80*80 grid cells was used to calculate the standard deviation of elevation at each field plot. High values indicates steep terrain while low values indicates flat terrain.

2.3.2 Topographical Modelling to Extract Wet Soils

The DEM was pre-processed using a three step breaching approach developed in Lidberg et al. (2017) in order to become hydrologically correct before it was used for hydrological modelling. Lidbergs approach was developed to be a reliable approach to correct the 2 m * 2 m Swedish DEM.

A flow pointer grid and a flow accumulation grid were extracted from the hydrologically correct DEM using Deterministic-8 (D8) (O'Callaghan and Mark 1984). D8 was chosen since it is computationally effective and the difference to more complex flow routing algorithm have been shown to be limited on high resolution DEMs (Leach et al. 2017). Streams were then extracted from the flow accumulation grid using stream initiation thresholds of 0.5 ha, 1 ha, 2 ha, 5 ha, 10 ha, 15 ha and 30 ha. Lake and river polygons from the property map were converted to raster and merged with the previously extracted raster streams in order to create source layers with cells that represent surface water.

2.3.3 Elevation Above Stream

Elevation above stream (EAS) is calculated using the source layer containing surface water described above, the same D8 pointer grid as used to extract streams, and the original DEM. The elevation above stream is calculated as the difference in elevation between a grid cell in the landscape and its nearest source cell that represent surface water, measured along the downslope flow path determined by the D8 pointer grid (Rennó et al. 2008). This was done for each of the source layers with the same stream initiation thresholds as mentioned above.

2.3.4 Depth to Water

Depth to water (DTW) is similar to previously described elevation above stream since both calculates an elevation difference from a source grid to surrounding landscape. The difference is that depth to water calculates the elevation along the least-cost-path instead of the downslope flow path determined by the D8 grid. The cost is the slope of the DEM calculated by the equation (1) described by (Murphy et al. 2008).

(Equation 1)

$$DTW\ (m) = [\sum \frac{dz_i}{dx_i} a]xc$$

Where *dz*/*dx* is the slope of a cell along the least-elevation path, *i* is a cell along the path, *a* equals 1 when the path crosses the cell parallel to cell boundaries and $\sqrt{2}$ when it crosses diagonally; *xc* represents the grid cell size (m).

2.3.4 Topographic Wetness Index

Topographic wetness index (TWI) describes how likely an area is to be wet based on its specific catchment area and local slope as described in equation (2). Where *As* is the specific catchment area and *slope* is the slope of the grid cells in degrees (Beven and Kirkby 1979).

(Equation 2)

$$TWI = \ln\left(\frac{As}{\tan(slope)}\right)$$

In this study it was calculated using the D-infinity flow routing algorithm (Tarboton 1997) which is better than D8 on coarser grids, and the wetness tool in Whitebox GAT 3.4. Since TWI is scale dependent we resampled the 2 m DEM to a 24 m DEM and a 48 m DEM as these has been found to be suitable resolutions for TWI calculations in the forested Krycklan catchment in northern Sweden (Ågren et al. 2014).

2.4 Other Factors Affecting the Hydrological Modelling

The quaternary deposit is an important factor for soil moisture since it determine permeability and drainage capacity of soils. Quaternary deposits were extracted from maps created by the Swedish Geological Survey. There are several maps of quaternary deposits in Sweden and the scale and coverage of these maps ranges from 1:25 000 (1.7 %), 1:50 000 (2.7 %) 1:100 000 (47 %), 1:200 000 (1.4 %), 1:250 000 (21.2 %), 1:750 000 (33.6 %) and 1:1 000 000 (100 %) (GET 2018). Some of these maps have significant overlap but the highest resolution map was always chosen in the overlapping areas. The quaternary deposits were merged by hydrological function into five main categories: till soils, peat soils, course sediments, fine sediments, and rock outcrops. Additionally open wetlands are more accurately mapped on the 1:12 500 scale property map so these were used in addition to the peat layer from the quaternary deposits map. There is considerable variability in runoff between different regions in Sweden and across seasons (Figure. 2). A high runoff should reflect higher groundwater levels which in turn could affect the distribution of wet soils. S-HYPE (Arheimer et al. 2011) was used to model seasonal and annual runoff in 33 605 subcatchments between 1982 and 2015. These variables will be referred to as "Spring", "Summer", "Autumn", "Winter" and "Average".

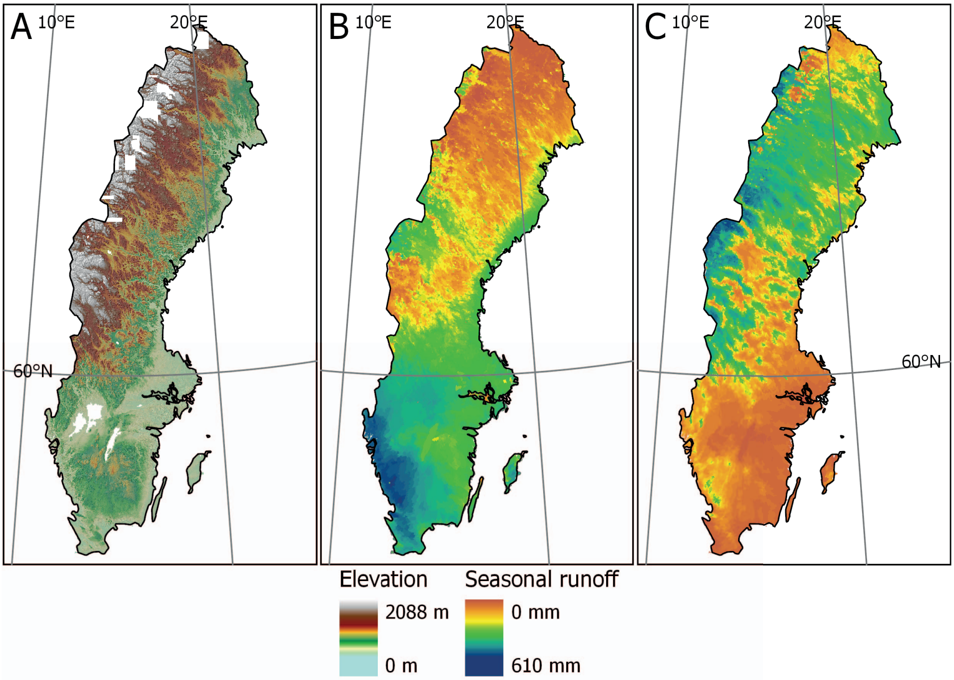

Figure 2. An example of the variability of the landscape and climate in Sweden that could affect the hydrological modelling (section 2.4) Here exemplified by; A) The Swedish national DEM B) Average winter runoff from the last 30 years. C) Average spring runoff from the last 30 years.

2.5 Machine Learning Classification of Wet Areas

There are many different ML algorithms available (Hastie et al. 2009) and their use for soil classification has already been evaluated (Maxwell et al. 2018). Four commonly used ML algorithms were tested to generate predictions of "wet" and "dry" soils: artificial neural network (Ripley 1996), random forest (Breiman 2001), support vector machine (Chang and Lin 2011) and naïve Bayes classification (Bhargavi and Jyothi 2009). The R package "Caret" (Kuhn et al. 2012) was used to evaluate all machine learners. Multicollinearity among variables was tested and variables with a correlation over 0.9 were excluded prior to analysis. The NFI dataset was split, randomly, into 75 % training data and 25 % test data and all ML algorithms where parameterized and tuned using a grid-search approach in combination with 10 fold cross validation to find the best fitting model. The tuned models were applied on the test dataset and evaluated using Cohen's kappa index of agreement.

Visual examination of maps has proved to be essential for assessing spatial ML predictions (Maxwell 2018). Therefore, as a compliment to the statistical results that were based on the NFI test plots, we also applied the trained models to classify soil moisture in the Krycklan catchment (Laudon et al. 2013). This catchment was chosen because the authors are familiar with the area and have conducted research there for over a decade. Wet areas and riparian zones have been mapped (Ågren et al. 2014), groundwater hot spots have been investigated (Leach et al. 2017), and culverts (Lidberg et al. 2017) have been mapped as well as temporal dynamics in the stream network (Ågren et al. 2015). The maps were used for visual inspection and compared to first-hand knowledge of the area.

2.6 Comparison with currently available maps

To be able to compare the performance of the ML wet area maps with today's wet area maps, their performance was also calculated (Table 2). We present data on the wet areas on the highest resolution map covering all of Sweden, the Swedish Property map (1:12 500) from Swedish Mapping, Cadastral and Land Registration Authority. In 2015, the Swedish Forest Agency (SFA) introduced a DTW map that is accessible online to private Swedish forest owners. The DTW map used by the SFA was calculated by setting two thresholds. The stream network initiation threshold which was set to 1 ha and the wet soil threshold defined as the depth to the modelled groundwater surface which was set to ≤1 m. These maps are presented in table 1 and Fig. 3 as reference.

3 Results

The wet area map from the property map (Figure 3A) only correctly classified 36 % of all "wet" field plots (Table 2). In total it classified 74 % of "dry"/"wet" areas correctly (Table 2). The introduction of the SFA DTW map (Figure 3B) meant that the accuracy of the wet area maps improved and correctly classified 73 % of all "wet" field plots but it to also classified 17 % of all "dry" field plots as "wet" (Table 2), indicating that the SFA DTW map is too wet. The ML maps (Figure 3C-F) performed even better, where random forest (Figure 3C) and artificial neural networks (Fig. 3E) produced the best maps and classified 84 % of the "dry"/"wet" soils correctly (Table 2). Some ML models also have the ability to map probability of their classifications. Figure 4 show the probability (%) of an area being classified as "wet".

Table 2. *Summary of accuracy of currently available maps and performance of the ML models when predicting the test dataset. Overall accuracy is the percentage of field plots that were correctly classified. Accuracy "wet" is the percentage of all "wet" field plots that were correctly classified as "wet" and accuracy "dry" is the percentage of all "dry" field plots that were correctly classified as "dry". The kappa value represents the level of agreement of two dataset corrected by chance.*

Wet area map	Overall accuracy	Accuracy "wet"	Accuracy "dry"	Kappa value
Wetlands from property map	74 %	36 %	99 %	0.39
SFA DTW map	79 %	73 %	82 %	0.55
ML Random forest	84 %	75 %	89 %	0.65
ML Support vector machine	82 %	68 %	90 %	0.60
ML Artificial neural network	84 %	74 %	90 %	0.65
ML Naïve Bayes	80 %	66 %	89 %	0.57

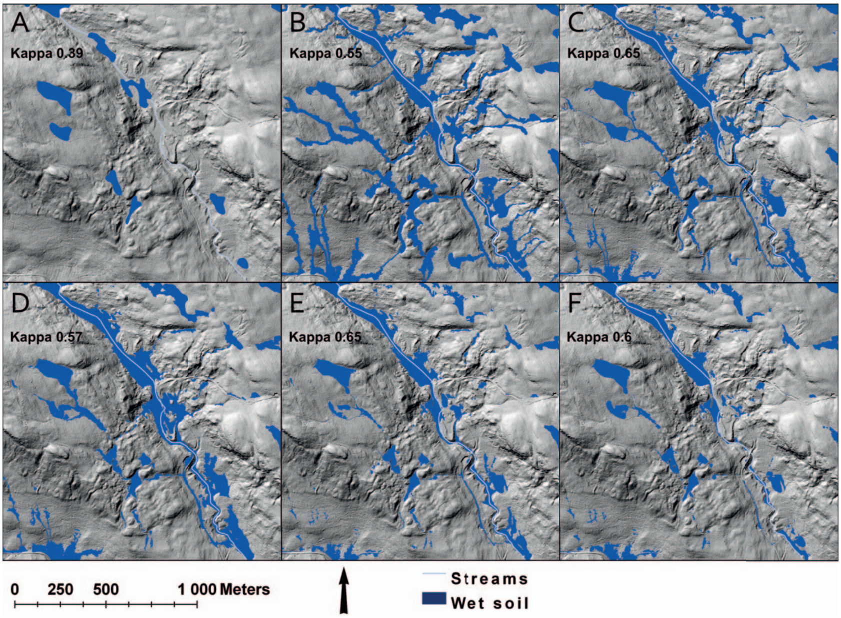

Figure 3. Wet areas are superimposed on a hillshade of a DEM in the Krycklan catchment. A) The wetlands from the property map, this map misses many of the wet areas. B) Swedish Forest Agency DTW map, this map has tendency to be too wet. Panel C-F shows the "wet" class using different machine learners; C) random forest D) naïve Bayes E) artificial neural network F) support vector machine. Even the worst ML map (naïve Bayes) performed better than the SFA DTW map, but random forest and artificial neural networks had the best results. The kappa values stated in the panels represents the maps performance for the entire forest landscape, even though the panels show a very small subsection of the Krycklan catchment.

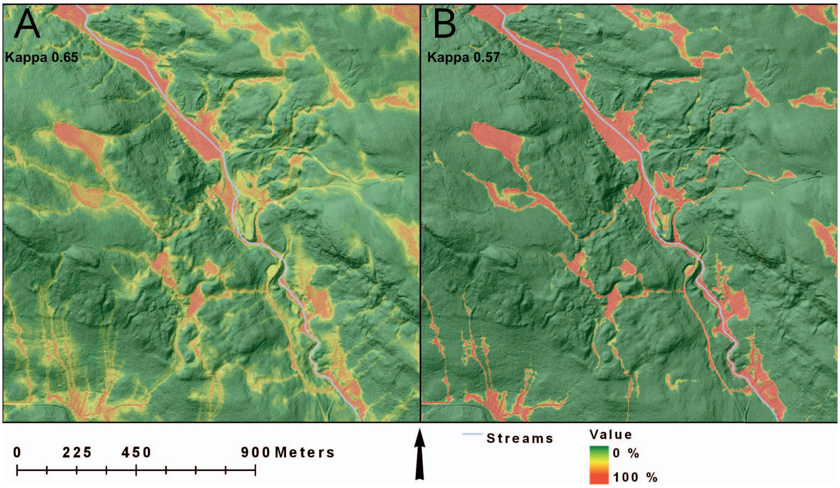

Figure 4. Example of probability (%) of predicted "wet" areas for one of the most accurate learner and the least accurate learner; A) random forest and B) Naïve Bayes. Areas with high probability of being classified as "wet" are red while areas with low probability of being classified as "wet" are green. The yellow areas in between is where the models are uncertain whether they should be classified as "wet" or "dry".

The importance of each variable varies and the contribution to learner's accuracy is estimated by excluding a variable and examine that effect on the overall learner behaviour. The learner will have lower accuracy if an important variable is missing. For example and in the case of random forest the three most important variables were standard deviation from elevation using a 5 cell moving window, a DTW map with 0.5 ha stream initiation threshold, and topographic wetness index from a 24 m DEM while the least important variables were the quaternary deposits (Figure 5).

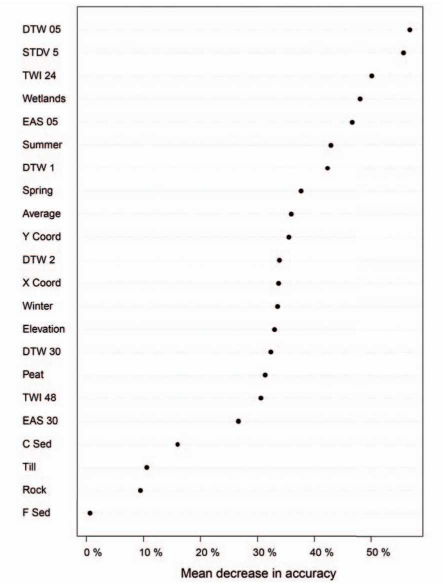

Figure 5. Important variables for the RF learner. Importance is measured as decrease in accuracy of the RF learner if the variable is excluded. Higher values indicate important variables. "DTW X" and "EAS X" refers to Depth to water and elevation above stream where X is the stream initiation threshold they are based on. "TWI 24" is topographical wetness index from a 24 m DEM while "TWI 48" is TWI from a 48 m DEM. "STDV" stands for standard deviation of elevation and the number specifies how many cells in the DEM that were used in the moving window. "Spring", "Summer", "Autumn", "Winter" is average seasonal runoff while "Average" is average annual runoff. "Wetlands" refers to the wetland layer from the property map while the quaternary deposits are labelled "Till", "Rock", "Peat", "C_Sed" (Course sediment), "F Sed" (Fine sediment). Finally "X_Coord", "Y_Coord" and "Elevation" are the coordinates and elevation. Variables that were described in the method section but not listed in Figure 5 were removed from the dataset due to multicollinearity.

4 Discussion

Several studies pointed that current maps of wet areas (Murphy et al. 2008) and stream networks (Benstead and Liegh 2012) are lacking in accuracy and has suggested modelling from DEMs to enhance performance. Here we found that only 36 % of all "wet" field plots were mapped as wetlands on the property map (Table 2) and since open wetlands and mires are easy to distinguish from aerial photos it's likely that the remaining 64 % of the "wet" plots are located on tree covered wetlands and in riparian zones. DTW maps have been introduced in Sweden and Canada as forest management planning tool (Ågren et al. 2014, 2015; Murphy, et al. 2008). The SFA DTW map performed better, but had a tendency towards being too wet since it had the lowest accuracy for "dry" field plots (Table 2). The major improvement with the SFA DTW map was that it also included wet areas near streams, the riparian soils (Figure 3B). However, there is regional and local variability in stream networks and extent of riparian soils depending on climate, soil permeability and terrain topography (Figure 2) (Ågren et al. 2014). This complex landscape variability can be captured by utilizing machine learners that uses automated data mining methods to discover patterns in large data sets (Heung et al. 2016). In our case 19 645 field plots on soil moisture were used to train learners to predict "wet" soils, pixel by pixel, throughout many different landscapes by combining the information in all input layers (Table 1).

Figure 5 showed that the three most important variables for the random forest learner were DTW, standard deviation from elevation using a 5 cell window (which reflects local topography), and topographic wetness index from a 24 m DEM. Average summer runoff also ranked high, indicating that both very small scale variations in local topography and large scale variations in climate needs to be considered when mapping wet areas. This agrees with other studies highlighting the complex controls of the distribution of wet soils on both local (Ågren et al. 2014) and regional scales (Jackson 1999). Using ML improved performance of the wet area maps and the two best maps; random forest (Figure 3C) and artificial neural networks (Figure 3E) classified 84 % of the "dry"/"wet" soils correctly (Table 2), with a kappa of 0.65. It should be noted and because the training dataset do not contain data from arable areas and urban areas, the models are only valid for two-thirds of the land area in Sweden. In other words, productive forestland and low-productive forestland (peatlands, pastures, thin soils and rock outcrops, areas close to and above the tree-line). Here we used the Swedish productive/non-productive forests landscape as a test bench to develop a methodology of using several digital terrain indices and many thresholds together with machine learning to develop more accurate maps of wet areas. The same methodology can be used in other countries that have a high resolution DEM and soil moisture data. Including additional terrain indices, satellite imagery and vegetation cover (Were 2015; Maxwell et al. 2017) could potentially also improve the accuracy of these maps in the future.

The developed maps have a high applicability and can be used to plan forest management in a way that reduces the effects on surface waters (Ågren et al. 2014). In Sweden, where cut-to-length forestry is the norm, forest soil trafficking is conducted by a harvester that cut trees to length and a forwarder that extracts timber, but also during thinning, fertilization, site preparation and harvest of logging residues for energy production (Ågren et al. 2015). This is also where the probability maps (Figure 4A show one of the maps with the best performance) can be used to plan off-road driving, especially the placement of extraction roads which suffer repeated heavy loads (a large laden forwarder can weigh 40 metric tons) during clear-cut. These extraction roads should not be placed in the red areas of Figure 4A to avoid soil damage. Yellow areas in Figure 4A are where the map is most likely to be inaccurate and extra care should be taken by the user while green areas are more suitable for driving.

The maps can also be used to balance the green energy targets (EU Renewable Energy Directive) and surface water protection (EU Water Framework Directive) by planning extraction of logging residues for energy production. On "wet" soils we recommend leaving the logging residues to reinforce the soils, by building slash mats to decrease the loads of the heavy machinery (Cambi et al. 2015) and thereby reduce the negative effects on surface waters. In "dry" areas, where soils have a higher bearing capacity, we suggest that the logging residues are harvested for bioenergy. The maps can be used in a first step of site planning but should be field validated during operations. There is also significant temporal variability in distributions of wet soils (Figure 2B&C), that are not taken into account in these maps (Figure 3). During winter when soils are frozen or during very dry conditions, it will be possible to traffic parts of the area marked as "wet". This is something practitioners are well aware of and utilize. However, the planning can be simplified by this maps that indicate the trafficability during periods of above average run off due to snow melt and rain. During extremely wet conditions almost all soils become wet or moist and are more susceptible to rut formation (Mohtashami et al. 2017). Therefore, it's common to find ruts outside the areas marked as "wet" in the maps (Figure 3B) (Mohtashami et al. 2017). However, forestry operations in the "dry" areas on the map (Figure 3) pose a smaller risk for increased sediment transport and nutrient/mercury leaching than operations in the "wet" areas where the connectivity to surface waters are higher (Ågren et al. 2015). The maps can also be used to plan hydrologically adapted protection zones near streams. Hydrologically adapted protection zones are better than using a fixed-width approach and offers an optimized site-specific riparian buffer when it comes to protection of ecological values (Gregory 1991) of riparian zones (Kuglerová et al. 2014). Hydrologically adapted riparian protection zones have also been found to be more cost-effective than fixed-widths zones (Tiwari et al. 2016). Hence, implementing the maps developed in this study (Figure 3&4) are a strategic option to meet both protection and production goals. Future research entails investigating if the maps can be used to further improve forest growth models used on a stand level or for national estimates, and whether they can be used in for example biogeochemical or ecological research.

5 Conclusions

Here we demonstrated that machine learning can be used to create new and more accurate high resolution maps of wet soils. These maps are better than previously used fixed threshold DTW maps. The new maps can for example be used to suggest machine free zones near streams and lakes in order to prevent rutting from forestry machines in order to reduce sediment, mercury and nutrient loads to downstream streams, lakes and sea.

References

Ågren, A. M., W. Lidberg, M. Strömgren, J. Ogilvie, and P. A. Arp. 2014. Evaluating digital terrain indices for soil wetness mapping - A Swedish case study. *Hydrology and Earth System Sciences 18*(9), 3623–3634. https://doi.org/10.5194/hess-18-3623-2014

Ågren, A. M., W. Lidberg, and E. Ring. 2015. Mapping temporal dynamics in a forest stream network—Implications for riparian forest management. *Forests*, *6*(9), 2982–3001. https://doi.org/10.3390/f6092982

Ansén, H. 2004. *Marktäckedata 2000*. Retrieved from http://www.scb.se/sv_/Hitta-statistik/Publiceringskalender/Visa-detaljerad-information/?publobjid=2465 (In Swedish, with English Summary)

Arheimer, B., J. Dahné, G. Lindström, L. Marklund, and J. Strömqvist. 2011. Multi-variable evaluation of an integrated model system covering Sweden (S-HYPE). *IAHS Publication*, *345*, 145–150.

Bhargavi, P., and S. Jyothi. 2009. Applying Naïve Bayes Data Mining Techinque for Classification of Agricultural Land Soils. IJCSNS International Journal of Computer Science and Network Security, 9 (8), 117-122.

Benstead, J. P., and D. S. Leigh. 2012. An expanded role for river networks, *Nature Geoscience*. 5: 678-679.

Beven, K.1986. Runoff production and flood frequency in catchments of order n: An alternative approach. Scale problems in hydrology (pp. 107–131). *Springer*, Dordrecht. https://doi.org/https://doi.org/10.1007/978-94-009-4678-1_6

Beven, K. J., and M.J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin*, 24(1), 43–69. https://doi.org/10.1080/02626667909491834

Breiman, L. 2001. Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Cambi, M., G . Certini, F. Neri, and E. Marchi. 2015. The impact of heavy traffic on forest soils: A review. *Forest Ecology and Management*. 338, 124-138. https://doi.org/10.1016/j.foreco.2014.11.022

Chang, C.C., and C.J. Lin. 2011. *LIBSVM:* A library for support vector machines. *ACM Trans. Intel. Syst. Tec*., 2, 27, https://doi.org/10.1145/1961189.1961199

Creed, I. F., and F.D. Beall. 2009. Distributed topographic indicators for predicting nitrogen export from headwater catchments. *Water Resources Research*, *45*(10), 2152-2160. https://doi.org/10.1029/2008WR007285

Creed, I. F., S. E. Sanford, Beall, L. A. Molot, and P. J. Dillon. 2003. Cryptic wetlands: integrating hidden wetlands in regression models of the export of dissolved organic carbon from forested landscapes. *Hydrological Processes*, *17*(18), 3629–3648. https://doi.org/10.1002/hyp.1357

Eklöf, K., R. Lidskog. and K. Bishop, 2016. Managing Swedish forestry's impact on mercury in fish: Defining the impact and mitigation measures. *Ambio*, *45*, 163–174. https://doi.org/10.1007/s13280-015-0752-7

Fransson, J. 2018. *SKOGSDATA 2018*. Umeå. Infra service, SLU, Uppsala, 2018. ISSN 0280-0543. (In Swedish)

GET. 2018. Quartneary deposits, Geological survey of Sweden, https://maps.slu.se/get

Gregory, S. V., F.J, Swanson, W. McKee, and K.W. Cummins. 1991. An ecosystem perspective of riparian zones. *BioScience*, *41*(8), 540–551. https://doi.org/10.2307/1311607

Güntner, A., J. Seibert, and S. Uhlenbrook. 2004. Modeling spatial patterns of saturated areas: An evaluation of different terrain indices. *Water Resources Research*, *40*(5), 15-23. https://doi.org/10.1029/2003WR002864

Guo, M., Li, J., C. Sheng, J. Xu, and L. Wu. 2017. A review of wetland remote sensing. *Sensors,* 17(4), 207-226, https://doi.org/10.3390/s17040777

Hastie, T., R. Tibshirani, and J. Friedman. 2009. The Elements of statistical learning. *Springer 2001*, *18*(4), 746. https://doi.org/10.1007/b94608

Heung, B., H.C. Ho, J. Zhang, A. Knudby, C.E. Bulmer, and M.G. Schmidt. 2016. An overview and comparison of machine-learning techniques for classification purposes in digital soil mapping. *Geoderma*, *265*, 62–77. https://doi.org/10.1016/j.geoderma.2015.11.014

Hjerdt, K. N., J.J. McDonnell, J. Seibert, and A. Rodhe. 2004. A new topographic index to quantify downslope controls on local drainage. *Water Resources Research*, *40*(5). https://doi.org/10.1029/2004WR003130

Jackson, T. J., D.M. Le Vine, A.Y. Hsu, A. Oldak, P.J. Starks, C.T. Swift, J.D. Isham, and M. Haken. 1999. Soil moisture mapping at regional scales using microwave radiometry: The Southern Great Plains Hydrology Experiment, IEEE *transactions on geoscience and remote sensing* 37 (5), 2136-2151

Kreutzweiser, D. P., and S.S Capell. 2001. Fine sediment deposition in streams after selective forest harvesting without riparian buffers. *Canadian Journal of Forest Research*, *31*(12), 2134–2142. https://doi.org/10.1139/x02-086

Kreutzweiser, D. P., P.W. Hazzlet, and J.M. Gunn. 2008. Logging impacts on the biogeochemistry of boreal forest soils and nutrient export to aquatic systems: A review. *Environmental Reviews*, *16*, 157-179. https://doi.org/10.1139/A08-006

Kuglerová, L., R. Jansson, A.M. Ågren, H. Laudon, and B. Malm-Renöfält. 2014. Groundwater discharge creates hotspots of riparian plant species richness in a boreal forest stream network. *Ecology*, *95*(3), 715–725. https://doi.org/10.1890/13-0363.1

Kuglerová, L., E.M. Hasselquist, J.S. Richardson, R.A. Sponseller, D.P. Kreutzweiser, and H. Laudon. 2017. Management perspectives on aqua incognita: Connectivity and cumulative effects of small natural and artificial streams in boreal forests. *Hydrological Processes*, *31*(23), 4238–4244. https://doi.org/10.1002/hyp.11281

Kuhn, M., J. Wing, S. Weston, A. Williams, C. Keefer, and A. Engelhardt. 2012. Caret: Classification and regression training. *Https://Cran.R-Project.Org/Package=Caret*. https://10.1088/0004-6256/148/1/21

Laudon, H., I. Taberman, A.M. Ågren., M. Futter, M. Ottosson-Löfvenius, and K. Bishop. 2013. The Krycklan Catchment Study - A flagship infrastructure for hydrology, biogeochemistry, and climate research in the boreal landscape. *Water Resources Research*, *49*(10), 7154–7158. https://doi.org/10.1002/wrcr.20520

Laudon, H., L. Kuglerova., R.A. Sponseller, M. Futter, A. Nordin, K. Bishop, T. Lundmark, G. Egnell, and A.M. Ågren. 2016. The role of biogeochemical hotspots, landscape heterogeneity, and hydrological connectivity for minimizing forestry effects on water quality. *Ambio*, *45*, 152-162. 11. https://doi.org/10.1007/s13280-015-0751-8

Leach, J. A., W. Lidberg, L. Kuglerová, A. Peralta-Tapia, A.M. Ågren, and H. Laudon. 2017. Evaluating topography-based predictions of shallow lateral groundwater discharge zones for a boreal lake-stream system. *Water Resources Research*, *53*(7), 5420–5437. https://doi.org/10.1002/2016WR019804

van Leeuwen, M., and M. Nieuwenhuis. 2010. Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research*. 129(4) 749–770. https://doi.org/10.1007/s10342-010-0381-4

Lidberg, W., M. Nilsson, T. Lundmark, and A.M. Ågren. 2017. Evaluating preprocessing methods of digital elevation models for hydrological modelling. *Hydrological Processes*, *31*(26), 4660–4668. https://doi.org/10.1002/hyp.11385

Maxwell, A. E., T.A. Warner, and F. Fang. 2018. Implementation of machine-learning classification in remote sensing: an applied review. *International Journal of Remote Sensing*, *39*(9), 2784–2817. https://doi.org/10.1080/01431161.2018.1433343

Moeslund, J. E., L. Arge, P.K. Bøcher, T. Dalgaard, R. Ejrnæs, M.V. Odgaard, and J.C. Svenning. 2013. Topographically controlled soil moisture drives plant diversity patterns within grasslands. *Biodiversity and Conservation*, *22*(10), 2151–2166. https://doi.org/10.1007/s10531-013-0442-3

Mohtashami, S., L. Eliasson, G. Jansson, and J. Sonesson. 2017. Influence of soil type, cartographic depth-to-water, road reinforcement and traffic intensity on rut formation in logging operations: A survey study in Sweden. *Silva Fennica*, *51*(5). https://doi.org/10.14214/sf.2018

Murphy, P., J. Ogilvie, C. Mark, R.M. Zhang Cheng Fu, Fan, and P. Arp. 2008. Improving forest operations planning through high-resolution flow-channel and wet-areas mapping. *Forestry Chronicle*, *84*(4), 568–574. https://doi.org/10.5558/tfc84568-4

Ocallaghan, J. F., and D.M. Mark. 1984. The Extraction of drainage Networks from digital elevation data. *Computer Vision Graphics and Image Processing*, *28*(3), 323–344. https://doi.org/Doi 10.1016/S0734-189x(84)80011-0

Rennó, C. D., A.D. Nobre, L.A. Cuartas, J.V. Soares, M.G. Hodnett, J. Tomasella, and M.J. Waterloo. 2008. HAND, a new terrain descriptor using SRTM-DEM: Mapping terra-firme rainforest environments in Amazonia. *Remote Sensing of Environment*, *112*(9), 3469–3481. https://doi.org/10.1016/j.rse.2008.03.018

Ripley, B. D., Pattern recognition and neural networks. 1996. Cambridge University press. https://doi.org/10.1017/CBO9780511812651

Sørensen, R., U. Zinko, and J. Seibert. 2006. On the calculation of the topographic wetness index: evaluation of different methods based on field observations. *Hydrology and Earth System Sciences*, *10*(1), 101–112. https://doi.org/10.5194/hess-10-101-2006

Tarboton, D. G. 1997. A new method for the determination of flow directions and upslope areas in grid digital elevation models. *Water Resources Research*, *33*(2), 309–319. https://doi.org/10.1029/96WR03137

Tiwari, T., J. Lundström, L. Kuglerová, H. Laudon, K. Öhman, and A.M. Ågren. 2016. Cost of riparian buffer zones: A comparison of hydrologically adapted site-specific riparian buffers with traditional fixed widths. *Water Resources Research*, *52*(2), 1056–1069. https://doi.org/10.1002/2015WR018014

Were, K., D.T. Bui, O.B. Dick, and B.R. Singh. 2015. A comparative assessment of support vector regression, artificial neural networks, and random forests for predicting and mapping soil organic carbon stocks across an Afromontane landscape, *Ecological Indicators*, 52, 394–403, https://doi.org/10.1016/j.ecolind.2014.12.028

Williamson, J.R., and W.A. Neilsen. 2000. The influence of forest site on rate and extent of soil compaction and profile disturbance of skid trails during ground-based harvesting. *Canadian Journal of Forest Research*. 30, 1196–1205.

IV

Digital mapping of hydrologically-adapted buffer strips on forested landscapes

William Lidberg[1*], Mats Nilsson[2], Erik Emilson[3], Irena Creed[4] and Anneli M. Ågren[1]

[1] Department of Forest Ecology and Management, Swedish University of Agricultural Sciences, Umeå, Sweden.

[2] Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden.

[3] Natural Resources Canada, Great Lakes Forestry Centre, Sault Ste. Marie, Ontario, Canada.

[4] School of Environment and Sustainability, University of Saskatchewan, Saskatoon, Saskatchewan, Canada.

Manuscript

Abstract

Forested riparian protection zones and machine-free areas near streams and lakes are commonly used to protect surface water during forestry activities. Fixed width protection zones are easy to plan and implement for managers but such tree-covered strips with uniform width do not take small scale variations into account. Here 36.8 km of field mapped riparian zones around headwater streams were used to evaluate the performance of topographically-delineated riparian protection zones (i.e., variable-width protection zones, a.k.a. hydrologically adapted protection zones). The best combinations of stream net-work and vertical thresholds for the topographically-delineated riparian zones were more accurate than any fixed width buffer at capturing the small-scale variations within the riparian zone.

However, since hydrologically-adapted buffers are based on modelled stream networks and rely on user set thresholds for stream initiation, it is necessary to adjust these maps for differences in subsurface geology, soil type and climate when working across physiographical regions. Machine learning could be successfully used to make these adjustments, but field data across larger spatial scales are required in order to train a machine learner.

Keywords: Wet area mapping; LiDAR; Riparian buffer; Soil classification; Digital elevation model; Random Forest

1 Introduction

Riparian zones constitutes the interface between terrestrial and aquatic environments and they provide numerous ecosystem services such as reduce export of nutrients (Gundersen et al. 2010) and suspended sediments from forestry operations (Kreutzweiser and Capell 2001). Riparian zones also regulate pH of streams (Cole et al. 2007), shading, temperature (Luke et al. 2007) and water quality (Kreutzweiser et al. 2013). Therefore, the utilization of protection zones (also known as riparian buffers) near streams are an important practice to protect surface waters in the boreal zone during forestry operations. Current management practices varies between countries due to different legislation (Ring et al. 2017) but fixed width buffers of 1-30 meter are commonly used along fluvial systems (Kuglerová et al. 2017). Fixed width buffers are easy to plan and implement for managers. Despite that they offer some protection they are often criticized since they are normally tree-covered strips with uniform age structure and width that do not take into account small scale variations (Richardson et al. 2012; Laudon et al. 2016). There are many reasons why a hydrologically-adapted, variable width buffer would give a better environmental protection. For example, some ecosystems are reliant on some periodic disturbance (Kreutzweiser et al. 2012) and some of this natural disturbance can be emulated by taking small-scale hydrological features into account during harvesting. Groundwater generally follows surface topography of compacted glacial till soils (Bishop et al. 2011) and converge in valleys. As these valleys leads towards the riparian zone they create discrete riparian inflow points (DRIPs) (Ploum et al. 2018). Leach et al. (2017) combined distributed temperature-sensing instrumentation with water isotope composition along a 1500 m headwater stream in boreal Sweden and showed that topography-based predictions of DRIPs were generally accurate. Furthermore, Kuglerová et al. (2014a) showed that that this local groundwater input increased vascular plant species richness between 15% and 20%, possibly due to an increase in soil pH and nitrogen availability in wet soils. This relationship between groundwater discharge and elevated plant species richness was observed from zero-order basins to a seventh-order river (Kuglerová et al. 2014a). Finally the hydrological connection between riparian zones and biogeochemical sources in upland soils means that riparian zones have an important role in regulating water quality across small spatial scales (Laudon et al. 2016). Implementing hydrologically adapted forest buffers can also increase tree production. Tiwari et al. (2016) compared the cost of fixed width and Hydrologically-Adapted Buffers (HAB) and concluded that protecting forest in HABs is cheaper per unit area compared to fixed-width buffers. This is because HABs contain more wetlands and low productive forest areas with more non-commercial tree species (e.g., birch). Small-scale hydrological variations need to be included into forest management but they are difficult to implement in practice due to the poor quality of current maps in forested landscapes. Maps are traditionally derived from aerial imagery where small streams (Bishop et al. 2008) and wetlands (Creed et al. 2003) are hard to detect due to dense forest canopy cover. As a result, many small hydrological features in forested areas are missing from current maps. Ågren et al. (2015) showed that, depending on season, 58% to 76 % of all streams were missing in a study catchment in northern Sweden. Additionally, Lidberg et al. (article 3 in this thesis) showed that current maps (the Swedish Property map) only captured 36% of the wet areas in the forest landscape. These unmapped streams and associated wet soils are a challenge for forest managers who are tasked with planning forestry operations such as protective zones near water.

Recent developments in remote sensing including Light Detection and Ranging (LiDAR) presented new possibilities to map small streams and associated wet soils using high resolution digital elevation models (DEMs) and topographical modelling. For example, Murphy et al. (2007) introduced a method to map riparian zones named Depth To Water (DTW) and Rennó et al. (2008) suggested another approach based on the Elevation Above nearest Stream cell (EAS). These methods have already proven to be useful and DTW maps are used today in for example Sweden and Canada to plan forestry operations such as driving near streams and lakes. DTW maps are based on stream networks so it is necessary to define the minimum catchment area required to form a stream head, also known as stream initiation threshold. Defining stream initiation thresholds has been difficult due to temporal hydrological dynamics (Ågren et al. 2015) and spatial distribution of soils (Ågren et al. 2014). This is especially prominent when working over larger scales and multiple physiographic regions.

In this study we aim to answer a number of research questions: Which modelling method - Depth to water (DTW) or Elevation above nearest stream cell (EAS) - is better for capturing the small scale variability in wet soils near stream channels? Is one method consistently better than the other or do they perform differently in different physiographic regions? Is it possible to model the variability of the riparian soils throughout the boreal zone using only one method and one threshold for the stream networks and lateral expansion of riparian soils, or do the models need to be adjusted to local conditions? To answer these questions, we field-mapped riparian soils in three different areas in the boreal zone and used this data to ground-truth available maps, using a range thresholds for both methods. A second aim of this study is to focus on DEM derived wet area map that are used in forest management today. As field mapping the riparian soils is very time consuming it's impossible to use field mapping as a method for generating riparian maps on a regional or national scale. When conducting forest management, forest companies need to manage the riparian buffers, and as a hydrologically adapted zone has many benefits, some forest companies have implemented wet area maps such as DTW or similar in their daily practice. However, how well do these maps perform? Do they capture the variability of the riparian zone? Can they be improved using the answers from our research questions?

2 Materials and Methods

2.1 Study sites and field data

To constrain the thresholds for the stream networks and lateral expansion of riparian soils along the stream networks, three study areas with different properties were selected for this study. Field data of riparian zones were collected in three catchments; Norralaån in central Sweden, Krycklan in northern Sweden and Black Brook in north-western New Brunswick, Canada (Figure 1). All study catchments lie in the boreal zone and have a history of forest management, however, the central part of the Krycklan catchment is not currently managed for forestry. Below follows a brief description of each study area and a summary of the topographical characteristics can be found in Table 1.

Table 1: *Topographical characteristics of the study areas and climate characteristics. Elevation and slope are derived from a 2 m DEM and stream order were based on a 0.5 ha stream initiation threshold.*

	Elevation (m)				Slope (°)				Climate		Stream order		
	Min	Max	Mean	SD	Min	Max	mean	SD	Precipitation mm/year	Mean annual temperature (°C)	Min	Max	Mean
Krycklan	176	296	234	29	0	56	6	5	614	1.8	1	6	3.3
Norralaån	22	279	138	61	0	74	7	6	600	3	1	8	3.7
Black Brook	234	392	315	29	0	75	10	7	1104	3.5	1	6	3.2

2.1.1 Krycklan

Krycklan is the northernmost study catchment situated in northern Sweden, and is a tributary to the Vindeln River. Krycklan is a 68 km^2 research catchment (Laudon et al. 2013) but in this study we only focus on the subsection of the catchment that was field-mapped. The bedrock is mainly metasediments/metagraywacke and the catchment was glaciated around 10 000 years ago. Quaternary deposits are dominated by till. Well-developed iron podzols dominate the forest floor while peat has developed in peatlands and near streams in the riparian zone. The topography is gentle compared to the other catchments as indicated by the low slope and standard deviation of the elevation (Table 1). The forests are dominated by Scots pine and Norway spruce and the land use is a mix of forestry and a protected research area.

2.1.2 Norralaån

Norrlanån is the largest catchment and has its outlet in the Baltic Sea. The bedrock is mainly metamorphic granitoid and the catchment was glaciated around 9 000 years ago. Quaternary deposits are dominated by till on hillsides while sorted glacial and post glacial sediments can be found in the valleys. Since the area has risen from the sea due to isostatic rebound wave washing has moved soil from hilltops and deposited finer sediment in lower areas of the catchment. The forests are dominated by Scots pine and Norway spruce and the main land-use is forestry followed by agriculture. Streams mapped in Norralaån were on average slightly larger than the other catchments based on stream order (Table 1).

2.1.3 Black Brook

The quaternary deposits in Black Brook is composed mainly of till with Ordovician–Devonian sedimentary rocks along generally undulating to rolling terrain, and deep, loamy soils in areas of low relief and shallow, stony soils in higher terrain (Erdozain et al. 2018). The dominating vegetation cover is sugar Maple, Yellow Birch and Balsam Fir (Furze et al. 2017). Black Brook was also glaciated like the other catchments until around 10 000 to 12 000 years ago.

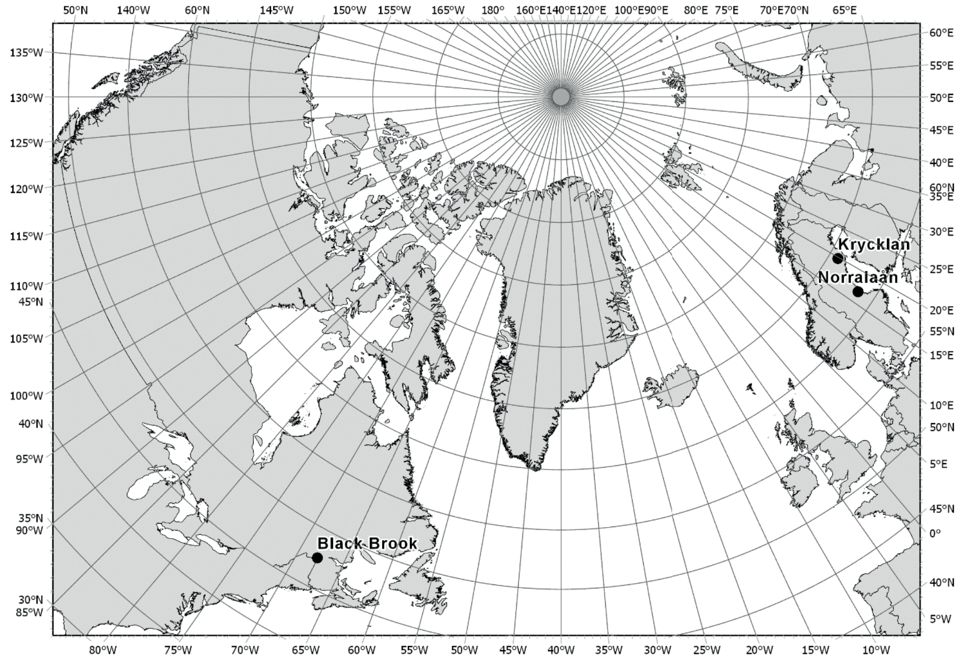

Figure 1: The three study catchments are marked by black points. Black Brook is located in north western New Brunswick, Canada while Norralaån and Krycklan are located in central and northern Sweden, respectively.

2.1.4 Field mapping of riparian zones

Field data of wet riparian zones were mapped along 36.8 km of streams (25 km in Norralaån, 6.3 km in Krycklan and 5.5 km in Black Brook) using high precision GPS and estimated soil moisture. There is significant temporal variability in the distributions of wet soils (Ågren et al. 2015) so vegetation communities were used as a proxy for average soil moisture conditions instead of direct measurements. The riparian zones were mapped by walking along the outer edge of wet areas and continuously logging GPS coordinates. This resulted in polygons encompassing wet riparian zones on both sides of the streams (Figure 2 and 3).

2.2 Digital mapping of riparian zones

2.2.1 Generating stream networks from a digital elevation model.

A 2 m DEM was created for Black Brook from a LiDAR point cloud using the tool “bare earth DEM” in Whitebox GAT (Lindsay 2014). The 2 m Swedish national DEM from the Swedish Mapping, Cadastral and Land Registration Authority, was used for both Swedish catchments. DEMs need to be pre-processed in order to become hydrologically correct before they can be used for hydrological modelling (Marks et al. 1984) and breaching has proven to be a reliable approach in Sweden (Lidberg et al. 2017). Therefore the DEMs were corrected by a two-step breaching approach:

1. Stream lines from the property map were burned across road lines from the property map using the tool “burn streams at roads” in Whitebox GAT 3.4 as described by (Lidberg et al. 2017).
2. Remaining sinks were resolved by the complete breaching algorithm developed by (Lindsay 2015) using Whitebox tools (Lindsay 2018).

A flow pointer grid and a flow accumulation grid were extracted from the hydrologically-corrected DEMs using a Deterministic-8 (D8) algorithm (O'Callaghan and Mark 1984). D8 was chosen since it is computationally-effective and the difference to more complex flow routing algorithm has been shown to be limited on high resolution DEMs (Leach et al. 2017). Streams were then extracted from the flow accumulation grid using stream initiation thresholds of 0.5 ha, 1 ha, 2 ha, 4 ha, 8 ha, 16 ha.

2.2.2 Generating hydrologically adapted buffer zones

2.2.2.1 Elevation Above Stream

Elevation above stream (EAS) generates a hydrologically adapted variable width riparian zone, with a wider wet zone in flat terrain and narrower in steep terrain (Figure 2). EAS was calculated using the source layer containing the extracted streams described above, the same D8 pointer grid as used to extract streams, and the original DEM. The elevation above stream was calculated as the difference in elevation between a grid cell in the landscape and its nearest source cell that represent surface water, measured along the downslope flow path determined by the D8 pointer grid (Rennó et al. 2008; Jencso et al. 2009; Nobre et al. 2011). This was done for each of the source layers described above with stream initiation thresholds of 0.5 ha to 16 ha, a low threshold means more stream channels and hence more wet areas. The expansion of the wet areas around the stream networks was also modelled using different vertical thresholds (0.5, 1 m, 1.5 m and 2 m), where a small threshold generates a narrower riparian zone and a high threshold generates a wider riparian zone.

2.2.2.2 Depth To Water

Depth to water (DTW) also generates a hydrologically adapted variable width riparian zone, with a wider wet riparian zone in flat terrain and narrower riparian zone in steep terrain (Figure 2b and Figure 2c). However, it is calculated in a different way. While both methods calculates an elevation difference from a source grid (stream grid) to surrounding landscape, depth to water calculates the elevation along the least-cost-path instead of the downslope flow path determined by a D8 grid. The cost is the slope of the DEM calculated by the equation (1) described by (Murphy et al. 2009; Murphy et al. 2011).

(Equation 1)

$$DTW\ (m) = [\sum \frac{dz_i}{dx_i} a]xc$$

Where dz/dx is the slope of a cell along the least-elevation path, $_i$ is a cell along the path, a equals 1 when the path crosses the cell parallel to cell boundaries and $\sqrt{2}$ when it crosses diagonally; xc represents the grid cell size (m). This was done for each of the source layers described above with stream initiation thresholds of 0.5 ha, 1 ha, 2 ha, 4 ha, 8 ha, and 16 ha. The expansion of the wet areas around the stream networks was modelled using different vertical thresholds (0.5, 1 m, 1.5 m and 2 m).

2.3 Maps currently used in management

In this section we compare different map sources available for forest companies in Sweden and Canada today. First we evaluate the performance of the topographical maps (the scale of the Swedish map was 1:12 500) and the scale of the Canadian map was 1:5 500). Fixed-width buffers of 5 m, 10 m, 20 m, 30 m and 40 m were applied to stream lines from the topographical maps. These were used as a baseline reference.

The Swedish Forest Agency (SFA) introduced a DTW map in 2015 that is accessible to private Swedish forest owners (SFA DTW). The DTW map used by the SFA was calculated by setting two thresholds, a stream initiation threshold which was set to 1 ha, and a height above stream threshold which was set to ≤1 m. A similar DTW map is available in New Brunswick, Canada, and is in use by the forest company J.D. Irving in Black Brook (NB DTW). This DTW map has a stream initiation threshold of 4 ha and height above stream threshold of ≤1 m.

Finally, we evaluated a version of the machine learning (ML) wet area map (WAM) suggested by Lidberg (article 3 in this thesis) in the two Swedish catchments. It could not be applied in Canada as the model has not been trained on the Canadian landscape. This machine learning wet area map (MLWAM) was predicted by a machine learner trained on field plots from the Swedish national forest inventory and is designed to capture all wet areas in the productive and non-productive forest landscape. This means that the map show both large open wetlands and riparian soils along stream networks and lakes, but here we only analyse how well it captures the riparian zone. In article 3 several machine learners were evaluated, here we only evaluate the machine learner Random Forest since it was one of the most accurate in article 3.

2.4 Statistical evaluation of the riparian maps

500 points were randomly generated for each hectare of field mapped riparian zone. Then an equal amount of points were randomly generated outside the riparian zone, but no further than 50 m from the outer edge of the field mapped riparian zone. This limit of 50 m was somewhat arbitrary but the idea was to avoid points on wetlands or other wet areas further away from the riparian zone, and also focus on the small scale variability near streams. All the maps described above were then extracted to each point. Points inside the field-mapped riparian zone were labelled as wet and the points outside were labelled as dry. Cohen's kappa index of agreement was used to evaluate the performance of each method compared to the field mapped riparian zones. Kappa is a more robust way to assess accuracy than simple percent agreements. All further mentions of accuracy is referring to the kappa value.

3 Results

3.1 Hydrologically adapted buffer zones

There was not one method that worked well across all catchments, rather each catchment required specific thresholds (Table 2). Most methods were more accurate in Black Brook compared to the Swedish catchments.

3.1.1 Krycklan

The best methods had a moderate agreement with the field data but the most accurate method was EAS from a 2 ha stream network and 2 m vertical threshold with a kappa value of 0.53. DTW from a 1 ha or a 2 ha stream network also performed well with marginally lower kappa values of 0.52. Fixed-width buffers were less accurate than DTW < 1 m and EAS < 2 m regardless of stream initiation threshold (Table 2).

3.1.2 Norralaån

All methods were most accurate when applied to the 2 ha stream network and DTW < 0.5 m was the most accurate method with a kappa value of 0.48. Most methods had a lower accuracy in Norralaån than the other catchments with only fair to moderate agreements with the field data. Note that a 10 m fixed-width buffer was more accurate than the most accurate EAS method.

3.1.3 Black Brook

All methods had a substantial agreement with the field data in Black Brook and the most accurate method was DTW < 1.5 m based on an 8 ha stream network with the kappa value 0.75. In fact all methods, including fixed width buffer, performed well using the 8 ha stream network in Black Brook.

Table 2. *Kappa values of the topographically derived riparian zones. Depth To Water (DTW), Elevation Above Stream (EAS) and Fixed-Width buffer (FW). The top row refers to the flow initiation threshold and the first column refers to the vertical threshold used. The best threshold for each method is highlighted in bold.*

Krycklan	*0,5 ha*	*1 ha*	*2 ha*	*4 ha*	*8 ha*	*16 ha*
DTW 0.5 m	0.5	0.48	0.43	0.4	0.38	0.36
DTW 1 m	0.49	**0.52**	**0.52**	0.5	0.48	0.46
DTW 1.5 m	0.41	0.46	0.50	0.50	0.5	0.48
DTW 2 m	0.31	0.38	0.45	0.46	0.45	0.45
EAS 0.5 m	0.33	0.30	0.27	0.24	0.23	0.22
EAS 1 m	0.49	0.46	0.44	0.41	0.39	0.39
EAS 1.5 m	0.52	0.51	0.51	0.48	0.46	0.46
EAS 2 m	0.50	0.51	**0.53**	0.5	0.49	0.49
FW 5 m	0.34	0.32	0.28	0.26	0.24	0.23
FW 10 m	**0.44**	0.42	0.39	0.36	0.34	0.33
FW 20 m	0.38	0.42	0.42	0.4	0.38	0.39
FW 40 m	0.14	0.21	0.26	0.28	0.27	0.3
Norrarlaån	*0.5 ha*	*1 ha*	*2 ha*	*4 ha*	*8 ha*	*16 ha*
DTW 0.5 m	0.44	0.47	**0.48**	0.47	0.45	0.42
DTW 1 m	0.35	0.4	0.44	0.44	0.43	0.41
DTW 1.5 m	0.26	0.31	0.35	0.36	0.37	0.37
DTW 2 m	0.19	0.23	0.27	0.29	0.3	0.31
EAS 0.5 m	0.25	0.3	0.25	0.24	0.22	0.20
EAS 1 m	0.29	0.31	**0.32**	0.31	0.29	0.27
EAS 1.5 m	0.27	0.29	0.31	0.31	0.29	0.28
EAS 2 m	0.23	0.26	0.28	0.28	0.27	0.27
FW 5 m	0.34	0.34	0.34	0.32	0.31	0.29
FW 10 m	0.40	0.42	**0.43**	0.41	0.41	0.38
FW 20 m	0.32	0.37	0.41	0.4	0.39	0.37
FW 40 m	0.10	0.15	0.19	0.20	0.21	0.21
Black Brook	*0.5 ha*	*1 ha*	*2 ha*	*4 ha*	*8 ha*	*16 ha*
DTW 0.5 m	0.59	0.58	0.57	0.56	0.56	0.54
DTW 1 m	0.63	0.67	0.7	0.72	0.72	0.71
DTW 1.5 m	0.58	0.65	0.71	0.73	**0.75**	0.74
DTW 2 m	0.52	0.6	0.67	0.70	0.73	0.73
EAS 0.5 m	0.4	0.37	0.36	0.34	0.33	0.32
EAS 1 m	0.59	0.57	0.56	0.53	0.53	0.52
EAS 1.5 m	0.66	**0.7**	0.66	0.65	0.64	0.63
EAS 2 m	0.66	0.69	**0.7**	0.69	**0.7**	**0.7**
FW 5 m	0.37	0.37	0.37	0.36	0.35	0.34
FW 10 m	0.49	0.53	0.57	0.56	0.57	0.55
FW 20 m	0.36	0.47	0.55	0.58	**0.6**	0.59
FW 40 m	0.08	0.17	0.26	0.3	0.33	0.33

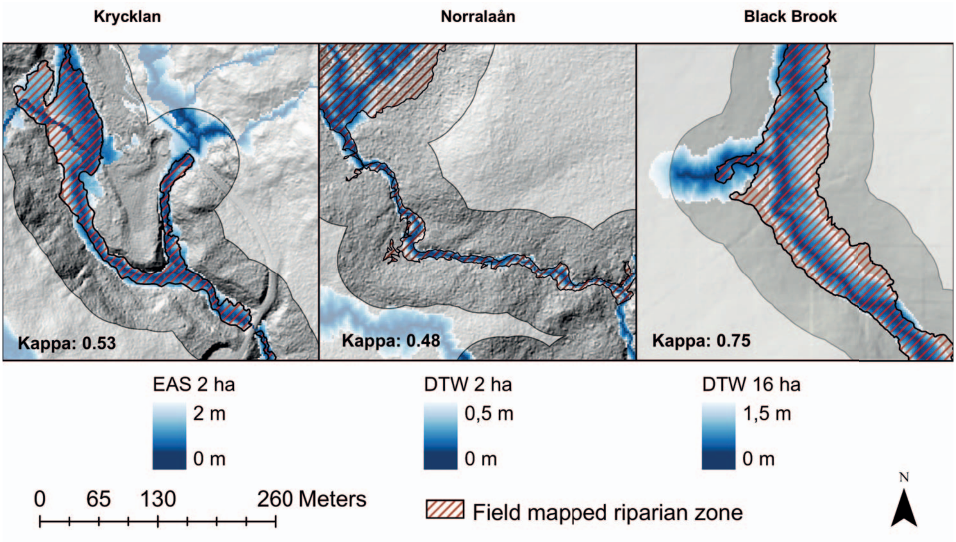

Figure 2: The most accurate combinations of stream initiation threshold and vertical threshold in all catchments. White shaded areas are more than 50 meter away from the field mapped riparian zone and were excluded from the statistical analysis in order to avoid wetlands or other wet areas further away from the riparian zone. The most accurate method in Krycklan was EAS 2ha with vertical threshold 2 m. The 2 ha stream network was also the most accurate in Norrarlaån but using DTW with a vertical threshold of 0.5 m. DTW was also the most accurate method in Black Brook but with a 8 ha stream network and 1.5 m vertical threshold. Note that the figure only show small subsections for each site, however, the kappa values stated on the map are evaluated on the entire areas.

3.2 Implications for management

Fixed-width buffers around streamlines from topographical maps only had a slight to fair agreement in the two Swedish catchments but performed better with fair to moderate agreement in Black Brook. However the DTW maps that are used in practice today performed better and both the SFA DTW map with national coverage of Sweden and the NB DTW map were more accurate than fixed width buffers from corresponding topographical map. The MLWAM suggested in article 3 was trained to map wet areas in general, and not riparian zones in particular, but still had a moderate agreement with field mapped riparian zones from both Krycklan and Norralaån and was slightly more accurate than the SFA DTW map (Table 3).

The currently used methods were applied in each catchment for visual evaluation since the statistical numbers alone do not tell the whole story (Figure 3). The baseline was the most accurate fixed-width buffer from current topographical maps. The SFA DTW map was used in the two Swedish catchments and the NB DTW map was used in the Black Brook catchments.

Table 3*: Kappa values of currently used maps of riparian zones in the study catchments. Topo X m, means fixed width buffers along the stream networks on topographical maps. SFA DTW and NB DTP are the depth to water maps in use by the Swedish Forest Agency and in New Brunswick, respectively. MLMAW is the machine learning wet area map developed by Lidberg et al. (article 3)*

	Krycklan	Norrarlaån	Black Brook
TOPO 5 m	0.13	0.20	0.29
TOPO 10 m	0.24	0.27	0.51
TOPO 20 m	0.33	0.27	0.59
TOPO 30 m	0.34	0.21	0.51
TOPO 40 m	0.29	0.14	0.36
SFA DTW	0.52	0.40	
NB DTW			0.72
MLWAM	0.54	0.41	

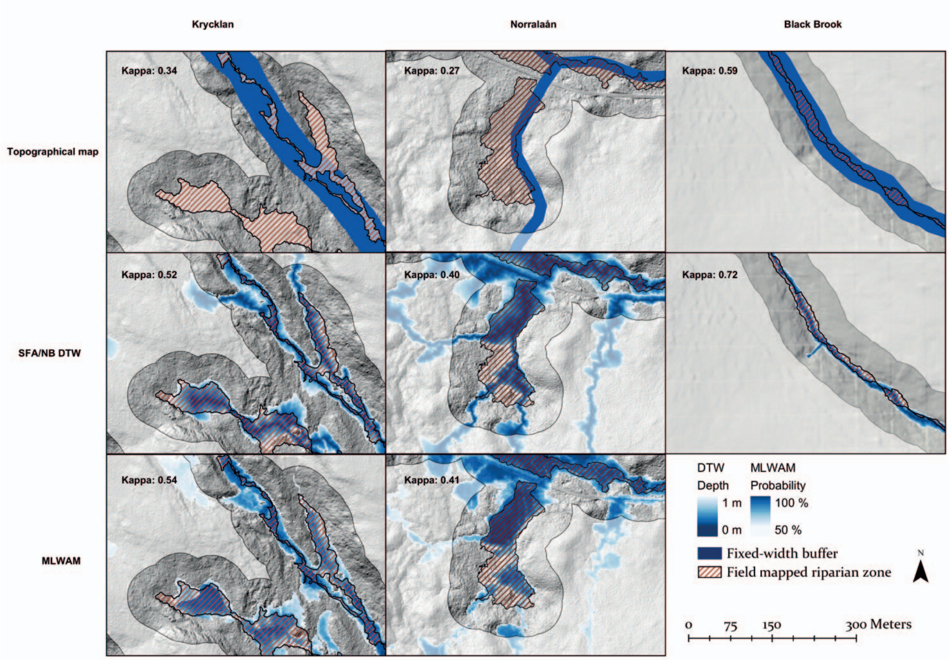

Figure 3. The top row is the most accurate fixed width-buffer from topographical maps in the respective catchment: 30 m in Krycklan, 10 m in Norrarlaån and 20 m in Black Brook. The second row is the DTW map used in practice today in respective area, light blue is the 1 m threshold and dark blue is DTW close to 0 m (depth to the modelled groundwater level). MLWAM is a wet area map suggested in article 3 of this thesis. The MLWAM is coloured by probability of a cell being classified as wet, light blue > 50 % probability and dark blue is close to 100 % probability. White shaded areas are more than 50 meter away from the field mapped riparian zone and were excluded from the statistical analysis in order to avoid wetlands or other wet areas further away from the riparian zone.

4 Discussion

Stream networks from current topographical maps are often missing small headwater streams in forested areas (Ågren et al. 2015) and mapping riparian zones around headwater streams using fixed width-buffers from these stream networks resulted in inaccurate maps (Table 5). This highlights the importance of a new approach to aid practitioners in planning riparian protection zones around these small streams (Murphy et al. 2008; Ågren et al. 2015; Ågren and Lidberg (article 2 in this thesis)). These headwaters make out the majority of any given stream network and are the capillaries of the stream networks and the associated riparian soils hence form an important contact area between land and surface waters. However, we know little about them and they are known as *Aqua Incognita* (Bishop et al. 2008; Kuglerová et al. 2017). It is of high interest both to scientist and to practitioners to be able to map these areas correctly. Chignell et al. (2018) recently used an integrative modelling approach to model riparian zones in the Cache la Poudre River watershed, Colorado, USA with the rather impressive under the curve values of 0.98. However most studies uses course resolution data (Baker et al. 2006) or focuses on riparian zones around large streams or rivers (Johansen et al. 2010; Jeong et al. 2016).

In this study we focused on relatively narrow riparian zones around headwater streams. We manually mapped wet riparian zones in three catchments in order to evaluate potential riparian protection zones derived from high resolution DEMs. The results from Black Brook were encouraging with kappa values of NB DTW of 0.72 while the results from Krycklan and Norralaån were less satisfying with SFA DTW kappa values of 0.52 and 0.40, respectively (Figure 3). Selecting the optimal method/threshold improved the maps slightly with kappa values of 0.75 in Black Brook, 0.53 in Krycklan and 0.48 in Norralaån (Figure 3). However, the variability in kappa values between regions highlights a need for more research in order to properly capture the small scale variability of the riparian zones around headwaters.

There are two ways of adjusting the DTW and EAS maps, the first is to alternate the length of the stream network. The position of stream channel heads have been shown to vary across physiographic regions (Elmore et al. 2013; Russell et al. 2015; Avcioglu et al. 2017; Jensen et al. 2017) but also across the relatively small (68 km^2) Krycklan catchment (Ågren et al. 2015). Several modelling studies have linked this control on channel head formation due to variability in slope (Elmore et al. 2013), soils (Ågren et al. 2014) and underlying geology (González-Ferreras and Barquín 2017; Jensen et al. 2017). However, there is also a seasonal and interanual variability in the location of stream heads (Ågren et al. 2015; Jensen et al. 2017). The recent PROSPER model use annual or monthly climate data, such as precipitation and temperature, and physiographic characteristics, such as soil types to model the probability of year-round flow in the Pacific North-west (with errors in the order of 20%) (Jaeger et al. 2019). Such studies have advanced understanding of the controls on stream networks, however, we identify two research gaps. First, more field inventories of stream heads in the northern boreal zone is needed to define the empirical relationships at higher latitudes, as most of this research has been conducted in the US. Second, we have to consider the scale of the DEMs used for modelling stream networks. Most of the studies mentioned above worked in a resolution of 10 to 30 m. As the number of high resolution DEMs increase with resolutions of 0.5 – 2 m, we may need to revisit the previous models to see if the result will still hold on a higher resolution. For example, Topographical Wetness Index (TWI) (Beven and Kirkby 1979), a hydrological mapping tool that have been used frequently during the past 40 years to model wet areas have been shown to only work at lower resolutions (Ågren et al. 2014).

In addition to adjust the stream initiation to local conditions the DTW and EAS maps can be adjusted by controlling the width away from the stream that is defined as a riparian area. In this modelling study, this was done by adjusting the vertical threshold to the modelled groundwater level. The DTW maps that are used in practice today use a threshold of 1 m. Ironically, that threshold was not the optimal threshold in any of the study areas, where 0.5, 1.5 and 2 m gave better results. In order to find empirical relationships on the controls on the distribution of riparian soils around stream networks, more research is needed. Another way forward can be to combine our understanding from different lower resolution DEMs (Jaeger et al. 2019) and satellite images (Chignell et al. 2017), with info from high (0.5-2 m) resolution DEMs. But, in order to create and test such empirical models more field datasets of riparian soils are needed. It's also necessary that the field data matches the resolution of the computer models. Hence, the use of a normal GPS which often have an accuracy of 15 m needs to be changed to a differential global positioning systems (DGPS) which provide sub meter accuracy.

Implementing HAB would benefit both environmental protection (Kuglerová et al. 2014b) and forest production (Tiwari et al. 2016). Designing buffer zones is mainly done in the field during snow-free seasons mostly by visual evaluation. If there were trustworthy maps delineating wet soils around stream networks they would facilitate planning of forest buffers and optimise off road driving with heavy forestry machines. Extraction roads could be planned in advanced to avoid deep rut formations in sensitive areas and stream crossings could be done in more suitable dry areas, where the riparian zone is relatively narrow, using technical aids. The use of logging residues can also be optimized and planed in advance to reduce negative impact on nearby surface water. Logging residues can be used to build slash mats in the most sensitive parts of the riparian zone to reduce rutting from heavy machines. Even small scale planning such as fertilization or seedling selection can be optimized within sites by soil moisture and seasonal water availability.

Ågren et al. (2015) showed that the stream network expands from 140 km during baseflow to 630 km during snowmelt and spring flood. During these expansive phases the ground water levels are elevated and almost all soils become wet or moist, and are more susceptible to rut formation (Mohtashami et al. 2017). Rutting is never desirable but ruts that's not connected to the riparian zone have a smaller risk for increased sediment transport and nutrient/mercury leaching than ruts in the riparian zone where the connectivity to surface waters are higher (Ågren et al. 2015). However, field mapped riparian zones used in this study was based on vegetation composition which reflects more average conditions.

4 Conclusions

We can draw two major conclusions from this study. First, the SFA/NB DTW maps and MLWAM maps do provide a clear improvement compared to the topographical maps (Table 3 and Figure 3). Secondly, our study show that there is still a need for further improvements of the mapping of small scale variability of the riparian zones around headwaters. LiDAR is still scarce in most of the boreal zone but there is a steady increase of national LiDAR campaigns. LiDAR based high resolution DEMs are becoming accessible in many countries (van Leeuwen and Nieuwenhuis 2010; Guo et al. 2017). Digital mapping of riparian zones could be a cost effective way to optimize management of riparian zones around headwater streams. Countries with intensive forestry often have extensive national forest inventories that could be used to train a machine learner to further increase the accuracy digital mapped riparian zones.

Acknowledgments

This project was financed by the Mistra's Future Forest program. Stiftelsen fonden för skogsvetenskaplig forskning, the Kempe foundation, VINNOVA and the EU InterReg Baltic Sea project WAMBAF. We would also like to thank Dave Kreutzweiser for collecting field data in Black Brook. Finally thanks to Jae Ogilvie and J.D. Irving, Ltd (JDI) for providing the LiDAR point cloud for the Black Brook catchment.

References

Ågren, A. M., W. Lidberg, M. Stromgren, J. Ogilvie, P. A. A. Arp, M. Strömgren, et al. 2014b. Evaluating digital terrain indices for soil wetness mapping - a Swedish case study. *Hydrology and Earth System Sciences* 18: 3623–3634. doi:10.5194/hess-18-3623-2014.

Ågren, A. M., W. Lidberg, E. Ring, M. A. Ågren, W. Lidberg, and E. Ring. 2015. Mapping Temporal Dynamics in a Forest Stream Network—Implications for Riparian Forest Management. *Forests* 6: 2982–3001. doi:10.3390/f6092982.

Avcioglu, B., C. J. Anderson, and L. Kalin. 2017. Evaluating the Slope-Area Method to Accurately Identify Stream Channel Heads in Three Physiographic Regions. *Journal of the American Water Resources Association* 53: 562–575. doi:10.1111/1752-1688.12512.

Baker, C., R. Lawrence., C. Montagne, and D. Patten. 2006. Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models. *Wetlands*. doi:10.1672/0277-5212(2006)26[465:MWARAU]2.0.CO;2.

Beven, K. J., and M. J. Kirkby. 1979. A physically based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin* 24: 43–69. doi:10.1080/02626667909491834.

Bishop, K., I. Buffam, M. Erlandsson, J. Folster, H. Laudon, J. Seibert, J. Temnerud, J. Fölster, et al. 2008. Aqua Incognita: the unknown headwaters. *Hydrological Processes* 22: 1239–1242. doi:10.1002/hyp.7049.

Bishop, K., J. Seibert, L. Nyberg, and A. Rodhe. 2011. Water storage in a till catchment. II: Implications of transmissivity feedback for flow paths and turnover times. *Hydrological Processes*. doi:10.1002/hyp.8355.

Chignell, S. M., M. W. Luizza, S. Skach, N. E. Young, and P. H. Evangelista. 2018. An integrative modeling approach to mapping wetlands and riparian areas in a heterogeneous Rocky Mountain watershed. *Remote Sensing in Ecology and Conservation*. doi:10.1002/rse2.63.

Cole, J. J., Y. T. Prairie, N. F. Caraco, W. H. McDowell, L. J. Tranvik, R. G. Striegl, C. M. Duarte, P. Kortelainen, et al. 2007. Plumbing the global carbon cycle: Integrating inland waters into the terrestrial carbon budget. *Ecosystems* 10: 171–184. doi:10.1007/s10021-006-9013-8.

Creed, I. F., S. E. Sanford, F. D. Beall, L. A. Molot, and P. J. Dillon. 2003. Cryptic wetlands: integrating hidden wetlands in regression models of the export of dissolved organic carbon from forested landscapes. *Hydrological Processes* 17: 3629–3648. doi:10.1002/hyp.1357.

Elmore, A. J., J. P. Julian, S. M. Guinn, and M. C. Fitzpatrick. 2013. Potential Stream Density in Mid-Atlantic U.S. Watersheds. *PLoS ONE*. doi:10.1371/journal.pone.0074819.

Erdozain, M., K. Kidd, D. Kreutzweiser, and P. Sibley. 2018. Linking stream ecosystem integrity to catchment and reach conditions in an intensively managed forest landscape. *Ecosphere*. doi:10.1002/ecs2.2278.

Furze, S., M. Castonguay, J. Ogilvie, M. Nasr, P. Cormier, R. Gagnon, G. Adams, and P. A. Arp. 2017. Assessing Soil-Related Black Spruce and White Spruce Plantation Productivity. *Open Journal of Forestry*. doi:10.4236/ojf.2017.72013.

González-Ferreras, A. M., and J. Barquín. 2017. Mapping the temporary and perennial character of whole river networks. *Water Resources Research*. doi:10.1002/2017WR020390.

Gundersen, P., A. Laurén, L. Finér, E. Ring, H. Koivusalo, M. Sætersdal, J. O. Weslien, B. D. Sigurdsson, et al. 2010. Environmental services provided from riparian forests in the nordic countries. *Ambio* 39: 555–566. doi:10.1007/s13280-010-0073-9.

Guo, M., J. Li, C. Sheng, J. Xu, and L. Wu. 2017. A review of wetland remote sensing. *Sensors (Switzerland)*. doi:10.3390/s17040777.

Jaeger, K. L., R. Sando, R. R. McShane, J. B. Dunham, D. P. Hockman-Wert, K. E. Kaiser, K. Hafen, J. C. Risley, et al. 2019. Probability of Streamflow Permanence Model (PROSPER): A spatially continuous model of annual streamflow permanence throughout the Pacific Northwest. *Journal of Hydrology X* 2. The Authors: 100005. doi:10.1016/j.hydroa.2018.100005.

Jencso, K. G., B. L. McGlynn, M. N. Gooseff, S. M. Wondzell, K. E. Bencala, and L. A. Marshall. 2009. Hydrologic connectivity between landscapes and streams: Transferring reach- and plot-scale understanding to the catchment scale. *Water Resources Research* 45. doi:10.1029/2008WR007225.

Jensen, C. K., K. J. McGuire, and P. S. Prince. 2017. Headwater stream length dynamics across four physiographic provinces of the Appalachian Highlands. *Hydrological Processes* 31: 3350–3363. doi:10.1002/hyp.11259.

Jeong, S. G., Y. Mo, H. G. Kim, C. H. Park, and D. K. Lee. 2016. Mapping riparian habitat using a combination ofremote-sensing techniques. *International Journal of Remote Sensing*. doi:10.1080/01431161.2016.1142685.

Johansen, K., S. Phinn, and C. Witte. 2010. Mapping of riparian zone attributes using discrete return LiDAR, QuickBird and SPOT-5 imagery: Assessing accuracy and costs. *Remote Sensing of Environment*. doi:10.1016/j.rse.2010.06.004.

Kreutzweiser, D., F. Beall, K. Webster, D. Thompson, and I. Creed. 2013. Impacts and prognosis of natural resource development on aquatic biodiversity in Canada's boreal zone. *Environmental Reviews*. doi:10.1139/er-2013-0044.

Kreutzweiser, D. P., and S. S. Capell. 2001. Fine sediment deposition in streams after selective forest harvesting without riparian buffers. *Canadian Journal of Forest Research* 31: 2134–2142. doi:10.1139/x02-086.

Kreutzweiser, D. P., P. K. Sibley, J. S. Richardson, and A. M. Gordon. 2012. Introduction and a theoretical basis for using disturbance by forest management activities to sustain aquatic ecosystems. *Freshwater Science*. doi:10.1899/11-114.1.

Kuglerová, L., R. Jansson, A. Ågren, H. Laudon, and B. Malm-Renöfält. 2014a. Groundwater discharge creates hotspots of riparian plant species richness in a boreal forest stream network. *Ecology* 95: 715–725. doi:10.1890/13-0363.1.

Kuglerová, L., A. Ågren, R. Jansson, and H. Laudon. 2014b. Towards optimizing riparian buffer zones: Ecological and biogeochemical implications for forest management. *Forest Ecology and Management*. doi:10.1016/j.foreco.2014.08.033.

Kuglerová, L., E. M. Hasselquist, J. S. Richardson, R. A. Sponseller, D. P. Kreutzweiser, and H. Laudon. 2017. Management perspectives on Aqua incognita: Connectivity and cumulative effects of small natural and artificial streams in boreal forests. *Hydrological Processes* 31: 4238–4244. doi:10.1002/hyp.11281.

Laudon, H., I. Taberman, A. Ågren, M. Futter, M. Ottosson-Löfvenius, and K. Bishop. 2013. The Krycklan Catchment Study - A flagship infrastructure for hydrology, biogeochemistry, and climate research in the boreal landscape. *Water Resources Research* 49: 7154–7158. doi:10.1002/wrcr.20520.

Laudon, H., L. Kuglerova, R. A. Sponseller, M. Futter, A. Nordin, K. Bishop, T. Lundmark, G. Egnell, et al. 2016. The role of biogeochemical hotspots, landscape heterogeneity, and hydrological connectivity for minimizing forestry effects on water quality. *Ambio* 45: 11. doi:10.1007/s13280-015-0751-8.

Leach, J. A. A., W. Lidberg, L. Kuglerová, A. Peralta-Tapia, A. Ågren, and H. Laudon. 2017. Evaluating topography-based predictions of shallow lateral groundwater discharge zones for a boreal lake-stream system. *Water Resources Research* 53: 5420–5437. doi:10.1002/2016WR019804.

van Leeuwen, M., and M. Nieuwenhuis. 2010. Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research*. doi:10.1007/s10342-010-0381-4.

Lidberg, W., M. Nilsson, T. Lundmark, and A. M. Ågren. 2017. Evaluating preprocessing methods of digital elevation models for hydrological modelling. *Hydrological Processes* 31: 4660–4668. doi:10.1002/hyp.11385.

Lindsay, J. B. 2014. The Whitebox Geospatial Analysis Tools Project and Open-Access GIS. *Conference: GIS Research UK 22nd Annual Conference, At Glasgow, UK*: 1–8. doi:10.13140/RG.2.1.1010.8962.

Lindsay, J. B. 2015. Efficient hybrid breaching-filling sink removalmethods for flow path enforcement in digitalelevation models. *Hydrological Processes*: 21. https://doi.org/10.1002/hyp.10648.

Lindsay, J. B. 2018. WhiteboxTools *User Manual*. Guelph. doi:10.13140/RG.2.2.22964.96648.

Luke, S. H., N. J. Luckai, J. M. Burke, and E. E. Prepas. 2007. Riparian areas in the Canadian boreal forest and linkages with water quality in streams. *Environmental Reviews* 15: 79–97. doi:10.1139/A07-001.

Marks, D., J. Dozier, and J. Frew. 1984. Automated Basin Delineation from Digital Elevation Data. *Geo-Processing* 2: 299–311.

Murphy, P., J. Ogilvie, K. Connor, and P. Arp. 2008. Mapping wetlands: A comparison of two different approaches for New Brunswick, Canada. *Wetlands* 27: 846–854. doi:10.1672/0277-5212(2007)27[846:MWACOT]2.0.CO;2.

Murphy, P. N. C., J. Ogilvie, and P. Arp. 2009. Topographic modelling of soil moisture conditions: a comparison and verification of two models. *European Journal of Soil Science* 60: 94–109. doi:10.1111/j.1365-2389.2008.01094.x.

Murphy, P. N. C., J. Ogilvie, F. R. Meng, B. White, J. S. Bhatti, and P. A. Arp. 2011. Modelling and mapping topographic variations in forest soils at high resolution: A case study. *Ecological Modelling* 222: 2314–2332. doi: 10.1016/j.ecolmodel.2011.01.003

Nobre, A. D., L. A. Cuartas, M. Hodnett, C. D. Rennó, G. Rodrigues, A. Silveira, M. Waterloo, and S. Saleska. 2011. Height Above the Nearest Drainage - a hydrologically relevant new terrain model. *Journal of Hydrology* 404: 13–29. doi:10.1016/j.jhydrol.2011.03.051.

Ocallaghan, J. F., and D. M. Mark. 1984. The Extraction of Drainage Networks from Digital Elevation Data. *Computer Vision Graphics and Image Processing* 28: 323–344. doi:doi 10.1016/S0734-189x(84)80011-0.

Rennó, C. D., A. D. Nobre, L. A. Cuartas, J. V. Soares, M. G. Hodnett, J. Tomasella, and M. J. Waterloo. 2008. HAND, a new terrain descriptor using SRTM-DEM: Mapping terra-firme rainforest environments in Amazonia. *Remote Sensing of Environment* 112: 3469–3481. doi:10.1016/j.rse.2008.03.018.

Richardson, J. S., R. J. Naiman, and P. A. Bisson. 2012. How did fixed-width buffers become standard practice for protecting freshwaters and their riparian areas from forest harvest practices? *Freshwater Science* 31: 232–238. doi:10.1899/11-031.1.

Ring, E., J. Johansson, C. Sandström, B. Bjarnadóttir, L. Finér, Z. Lībiete, E. Lode, I. Stupak. 2017. Mapping policies for surface water protection zones on forest land in the Nordic–Baltic region: Large differences in prescriptiveness and zone width. *Ambio* 46: 878–893. doi:10.1007/s13280-017-0924-8.

Russell, P. P., S. M. Gale, B. Muñoz, J. R. Dorney, and M. J. Rubino. 2015. A spatially explicit model for mapping headwater streams. *Journal of the American Water Resources Association*. doi:10.1111/jawr.12250.

Tiwari, T., J. Lundström, L. Kuglerova, H. Laudon, K. Lidhman, and A. M. Ågren. 2016. Cost of riparian buffer zones: A comparison of hydrologically adapted site-specific riparian buffers with traditional fixed widths. *Water Resources Research* 52: 1056–1069. doi:10.1002/2015WR018014.