Evaluating digital terrain indices for soil wetness mapping – a Swedish case study

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Abstract

Driving with forestry machines on wet soils within and near stream and lake buffers can cause soil disturbances, i.e. rutting and compaction. This – in turn – can lead to increased surface flow, thereby facilitating the leaking of unwanted substances into downstream environments. Wet soils in mires, near streams and lakes have particularly low bearing capacity and are more susceptible to rutting. It is important to model and map the extent of these areas and associated wetness variations. This can be done with adequate reliability using high resolution digital elevation model (DEM). In this article, we report on several digital terrain indices to predict soil wetness by wet-area locations. We varied the resolution of these indices to test what scale produces the best possible wet-areas mapping conformance. We found that topographic wetness index (TWI) and the newly developed cartographic depth-to-water index ($D_{TW}$) were the best soil wetness predictors. While the TWI derivations were sensitive to scale, the $D_{TW}$ derivations were not and were therefore numerically fairly robust. Since the $D_{TW}$ derivations vary by the area threshold used for setting stream flow initiation we found that the optimal threshold values varied by landform, e.g., 1–2 ha for till-derived landforms vs. 8 –16 ha for a coarse-textured alluvial floodplain.

1 Introduction

It is well established that forestry, agriculture, transportation corridor (roads, trails), and other land-use practices can affect water quality (Buttle, 2011; Ahtiainen, 1992; Laudon et al., 2009; Schelker et al., 2012). One major threat for surface waters is soil erosion and subsequent increases in sediment loads. This, in turn, increases water turbidity and cover gravelly stream beds (Lisle, 1989), thereby decreasing the reproductive success of fresh-water fish (Burkehead and Jelks, 2001; Soulsby et al., 2001) and macro invertebrates (Lemly, 1982). In forestry, primary sediment sources are road crossings (Kreutzweiser and Capell, 2001), logging roads, skidder trails (Sidle et al., 2006), and...
ditching activities (Prevost et al., 1999). Rutting along slopes and wet soils can also affect water quality and aquatic habitat. For example, Munthe and Hultberg (2004) found that heavy forestry machinery traffic disturbs the soil, changes the water flow paths, and increases the local stream concentration of methylmercury (MeHg) with 600% over a period of at least 3 years. Bishop et al. (2009) estimated that 9–23% of the Hg in fish in Sweden is associated with the increased Hg outputs from clear-cutting. A study by Kronberg (2014) calculated that MeHg loads increased by 14% after clear-cutting. To mitigate this effect, soil scarification and driving in wet and moist areas and across flow channels without brush mats should be avoided. Until now, areas that are sensitive to soil disturbances have not yet been mapped at resolutions sufficient to be included in forestry planning operations. Doing so, however, would greatly reduce environmentally and economically costly forest traffic “surprises”, and would be in compliance with a new policy from the Swedish forest industry suggesting that “driving on forest soils should be planned according to soil conditions, surface waters and cultural heritage”. In this policy, rutting is classified as acceptable vs. unacceptable depending on the environmental implications for each site. Any rutting in contact with or near streams and lakes is unacceptable (Berg et al., 2010).

This study compares several digitally derived soil wetness indices in terms of their conformance to actual wet-area conditions around streams and lakes. For references and recent developments pertaining to these indices, see Murphy et al. (2009, 2011), Tarboton (1997), Ma et al. (2010), Blöschl and Sivapalan, 1995). The areas for this case study are within the Krycklan catchment, Sweden (Fig. 1). The aim of this study is to develop a framework for mapping wet soils at high resolution, thereby improving the planning of forest operations, especially near streams and lakes.
2 Methods

2.1 Soil wetness transects

For the soil wetness survey we did not measure soil wetness but mapped indicators, along line transects on three areas within the well-studied Krycklan catchment (Laudon et al., 2013) (Fig. 1). The field survey was conducted 10–14 October 2011, during that period discharge measured at site C7 (Laudon et al., 2013) was 0.84 (Standard deviation, SD = 0.13) mm day\(^{-1}\) which matched the long term average 0.84 (SD = 1.53) mm day\(^{-1}\) for the period 1981–2013. In Area 1, eight 800–850 m transects were placed perpendicular to a number of ridges. This area is glaciated and till is dominating the soils, apart from a flat wetland located north east. The direction of the ice flow from northwest to southeast can be seen on the DEM in Fig. 3 by the orientation of the craig tails and drumlins. In Area 2, twelve transects were placed on a long ridge-to-valley hillslope. Till covers the hillslope, decreasing in thickness towards the top according to the Quaternary deposits map (1 : 100 000, Geological Survey of Sweden, Uppsala, Sweden). Area 2 also includes a mire at the bottom of the hill. In Area 3, eight 500 m transects were placed to cross the valley and floodplain of the Krycklan stream. The floodplain is filled with ice-river alluvium, containing mostly sand, gravel and boulders. The stream has cut down through the ice-river sediments forming ravines that become deeper towards the south. The upper east side of this valley is dominated by a moraine.

The geographical positions for each plot along the transect lines were determined using hand-held GPS, with an accuracy of < 10 m in 95% of the measurements. Soil wetness was mapped according to the instructions for the Swedish Survey of Forest Soils (Anon, 2013). Temporal variations from dry to wet were to be ignored in favour of determining the underlying soil wetness regime and the related soil wetness classes, i.e., wet, moist, mesic-moist, mesic and dry soil, for full definitions see (http://www-markinfo.slu.se/eng/soildes/fukt/skfukt1.html). The process involved estimating the depth to the average water table level during the vegetation period, in reference to the elevation rise away from open water features (lakes, streams),
wetlands, ditches, and wet obligatory (hydric) vegetation. In short the five wetness classes were defined as: on wet soils, (i) there are frequent permanent water pools, (ii) one cannot walk dry-footed in low shoes; (iii) soils are organic (often fens); (iv) conifers occur only occasionally. On moist soils, (i) the groundwater table is on average at less than 1 m depth, (ii) one can walk dry-footed in low shoes, provided one can step on tussocks in the wetter parts; (iii) wetland mosses (e.g. *Sphagnum* sp.) dominate local depressions (pits), and trees often show a coarse root system above ground (germination point above soil); (iv) ditches are common; (v) soils range from organic (generally fens) to mineral (generally humus-podsols). On mesic-moist soils, (i) the groundwater table is also on average at less than 1 m depth, (ii) but one can walk dry-footed in low shoes over the entire vegetation area, except after heavy rain or snowmelt; (iii) areas with wetland mosses (e.g. *Sphagnum* sp., *Polytrichum commune*, *Polytrichastrum formosum*, *Polytrichastrum longisetum*) are common; (iv) trees show a coarse root system above ground (germination point above soil); (v) soils podsolic (humo-ferric to humic podsols); (vi) the mineral soil is covered by a thick peaty mor (thicker than on mesic soils). On mesic soils, (i) the groundwater table is on average at 1–2 m depth; (ii) one can walk dry-footed in low shoes over the area even after heavy rains/snowmelt; (iii) the bottom layer consists mainly of dryland mosses (e.g. *Pleurozium schreberi*, *Hylocomium splendens*, *Dicranum scoparium*); (iv) ferric podsols with a thin (4–10 cm) humus layer (mor) are common; (v) the bleached horizon is grey-white and well delineated against the rust-yellow, rust-red or brownish rust-red B horizon (the darker the colour, the wetter the soil). On dry soils, (i) the groundwater table is deeper than 1 m; (ii) dry soils are found on eskers, hills, marked crowns and ridge crests; (iii) the soils tend to be coarse in texture and include lithosol, boulder soil, and iron podsol formations, generally covered with a thin humus blanket on a thin bleached horizon; (iv) there can be significant bedrock exposure.
2.2 LiDAR acquisition and digital elevation model (DEM)

Since 2009, Lantmäteriet, the Swedish Mapping, Cadastral and Land Registration Authority, is generating high-resolution elevation scans using LiDAR technology (Light Detection and Ranging) for all of Sweden, with a point density of 0.5–1 points per m$^2$, an average xy point error of 0.4 m (SWEREF 99 TM), and a vertical accuracy of 0.1 m (RH 2000). The scanning of the study area was conducted during optimal conditions: after leaf fall and before snow cover, 11–14 October 2010. A 2 m x 2 m bare-ground Digital Elevation Model (or 2 m DEM for short), with an average elevation error of 0.5 m, was generated from the ground elevation returns of the LiDAR signals. This was done through triangulated irregular network (TIN) interpolation. The resulting DEM was hydrographically corrected by automatically breaching roadside impoundments and by removing DEM depression artifacts.

2.3 DEM processing

All DEM processing was done with ArcGIS 9.3 modeling tools and TauDEM 5.0. The 2 m DEM was used to derive the following terrain attributes in raster format: flow direction, aspect, curvature, plan curvature, cartographic depth-to-water ($D_{TW}$), flat areas, landform, puddles, toeslope, topographic position index (TPI) and topographic wetness index (TWI). These indices were evaluated at resolutions varying from 2 to 100 m.

Aspect was calculated on a 2, 4, 8, 16, 32 m resampled DEM, using bilinear interpolation. Since the aspect is given in degrees with both 0 and 360° facing north, aspect was computed in radians and then sine transformed to range from $-1$ to 1. Curvature was derived from the 2 m DEM in the direction of slope gradient (profile curvature) and perpendicular to the gradient (plan curvature). Profile curvature affects the acceleration and deceleration of flow while the plan curvature affects the convergence and divergence of the flow. Both curvature types were derived using windows spanning 3, 7 and 9 cells. A flatness index was derived from the 2 m DEM
using the zonal statistics function to determine the standard deviation of elevations within a radius of 10, 20, and 30 m. A low standard deviation indicates a flat area. **Puddles** within the DEM were identified by subtracting the 2 m DEM from a smoothed DEM, with smoothing referring to the mean elevations within a rectangle of 3 × 3, 5 × 5, 7 × 7, and 9 × 9 cells. Negative differences locate local puddles. **Toe-slopes** were DEM-derived by creating a 0, 1 raster, with toe-slope cells marked as 1 and all other cells marked as 0. This was done twice by smoothing the 2 × 2 m DEM across 3 × 3 cells and 9 × 9 cells, and selecting those cells with a slope change of 11–20°. Topographic position index (TPI) compares the elevation of a cell to the mean elevation to the surrounding cells in a specified area. Positive values represent ridges and negative TPI values represent valleys while flat areas have a value near zero. TPI is scale dependent and was determined from the 2 m DEM using a cell moving window average of 17, 30, and 50 cells. Topographic landform classes (TLF) The TPI values were classified into 6 topographic landform classes (TLF) using the definition by (Weiss, 2001): 1 Ridge (STDEV > 1). 2 upper slope (0.5 < STDEV ≤ 1); 3 middle slope (−0.5 < STDEV < 0.5, slope > 5°); 4 flat slope (−0.5 ≤ STDEV < 0.5, slope ≤ 5°); lower slopes (−1.0 ≤ STDEV < −0.5); 6 valley (STDEV < −1). The numerically higher landform classes refer to lower slopes or valleys and would therefore be wetter than the numerically lower landform classes (ridges, upper slopes). Topographic wetness index (TWI) (Beven and Kirkby, 1979) was calculated using TauDEM 5.0.6. TWI was defined as: $\text{TWI} = \ln(a/\tan \beta)$ where $a$ is the D∞ specific catchment area (contributing area per unit contour length) and $\beta$ is the D∞-slope, in radians (Tarboton, 1997). Flow in flat areas was calculated according to Garbrecht and Martz (1997). That means that a high TWI indicates areas were much water accumulates and the slope is low. In contrast, steep slopes drain water and are therefore drier as indicated by low TWI. Since estimating slope and therefore TWI is strongly scale dependent (Blöschl and Sivapalan, 1995), it was necessary to repeat the TWI derivation by smoothing the 2 m DEM using moving windows with 2, 4, 6, 10, 14, 24, 50, and 100 m diameters. Doing so generated 2, 4, 6, 10, 14, 24, 50, and 100 m spaced TWI grids, which were then
interpolated back to 2 m resolution by way of bilinear interpolation. Cartographic depth-to-water ($D_{TW}$) index calculates the depth (m) down to a modeled groundwater table throughout the landscape, in reference to zero depths at all locations where water is known or estimated to be at the surface. This index (Murphy et al., 2009, 2011) was derived from the 2 m DEM as follows: first the DEM was filled and the flow direction and flow accumulation data layers were generated using the D8 method (Jenson and Domingue, 1988; O’Callaghan and Mark, 1984). The resulting flow accumulation raster was used to derive the topographically defined flow channel networks with 0.5, 1, 2, 2.5, 4, 5, 8, 10, and 16 ha flow initiation thresholds. $D_{TW}$ was then determined for each of the resulting flow networks by determining the least elevational differences between each DEM cell and its nearest stream cell according to the least-elevation path between these cells. Mathematically,

$$D_{TW} = \left[ \sum \frac{dz_i}{dx_i} a \right] x_c$$

(1)

where $dz/dx$ is the slope of a cell along the least-elevation path, $i$ is a cell along the path, $a$ is 1 when the path crosses the cell parallel to the cell boundaries and 1.414214 when it crosses diagonally; $x_c$ represents the grid cell size (m).

2.4 Validation of terrain indices against field mapped soil wetness

2.4.1 Data preprocessing

Each variable was tested for normality using the Kolmogorov–Smirnow test (IBM SPSS Statistics 19). As a result, $D_{TW}$, TWI, TPI and flatness indices were log transformed to fit normality and to reduce the heteroscedasticity of model residuals. All index variables were scaled and centered using $z$ scores (Eriksson et al., 2006a). Landform types were entered into the analyses as dummy variables.
2.4.2 Orthogonal projections to latent structures (OPLS)

The transect data for soil wetness were used to validate the digital terrain indices through direct point-by-point comparisons (of each \(2 \times 2\) m cell). This was done using the multivariate statistical program SIMCA-P+ 12.0.1, Umetrics, Umeå. The statistical tests were done using the recently developed OPLS (orthogonal projections to latent structures) method (Eriksson et al., 2006a, b). This method, which is similar to principal component analysis, separates the variations of the predictors \(X\) (the DEM-derived soil wetness predictors) into two parts: one part that is predictive of \(Y\) (the field-determined soil wetness estimates), and one part that is orthogonal, i.e., not related to \(Y\). In the loading plot, \(X\) variables with loadings that score high or low on the predictive axis are highly positively or negatively correlated to \(Y\) (Fig. 2). In SIMCA-P+, the program also calculates the influence of each \(X\) variable in the model, called variable importance in projection (VIP). Variables with large VIP, i.e., larger than 1, are the most relevant for explaining \(Y\). In the OPLS loading plots of Fig. 2, variables with VIP > 1 and < 1 are marked by black and grey text, respectively.

2.4.3 Confusion matrix

The overall conformance of \(D_{TW} \leq 1\) m relative to the wet and moist soils within Areas 1, 2 and 3 was further tested by way of a confusion matrix. This was done by way of 4 \(D_{TW}\) performance groups: (i) True Positive (\(T_P\)) when the \(D_{TW} \leq 1\) m correctly identified a wet area; (ii) True Negative (\(T_N\)) when \(D_{TW} > 1\) m correctly identified a dry area; (iii) False Positive (\(F_P\)) or Type I error, i.e. when \(D_{TW} \leq 1\) m predicts wet soils when the soils are actually dry; (iv) False Negative (\(F_N\)), or type II error, i.e. \(D_{TW} > 1\) m predicts dry soils when the soils are actually wet. These tests were applied to the \(D_{TW}\) determinations as these vary by the \(D_{TW}\)-defining flow networks, using the flow-initiation thresholds from 0.5 to 16 ha. The accuracy (\(A_{CC}\)), or efficiency, of each of the \(D_{TW} \leq 1\) or > 1 m
locations was assessed by way of:

\[ A_{CC} = \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} \]  

(2)

Also used was the Matthews correlation coefficient \( (M_{CC}) \) for which a value of 1 indicates a perfect fit, a 0 yields a results that is no better than random prediction, and -1 indicates a perfect negative correlation. \( M_{CC} \) was calculated as:

\[ M_{CC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \]  

(3)

Equations (2) and (3) were also used to determine the \( A_{CC} \) and \( M_{CC} \) values for the currently used 1 : 12500 property map for Sweden in reference to the field determined soil wetness values. This map contains all officially recognized surface water and wetland features, including mires.

3 Results

The OPLS model generated models with high predictability (high R2Y and Q2) for soil wetness for Areas 1, 2 and 3 (Fig. 2). The two terrain indices that correlated best with the field-determined soil wetness data were TWI and \( D_{TW} \). The effect of DEM resolution on the soil wetness predictor performance of these two indices can be seen from Fig. 2. Here, the \( D_{TW} \) values cluster closely together along the negative portion of the predictive soil wetness axis \( (pq[1]) \). In contrast, the scale-dispersed TWI values cut across the positive side of the horizontal axis, with TWI showing the strongest soil wetness prediction performance when derived from the 24 m (Area 1, Area 3) or 50 m (Area 2) DEMs. In particular, TWI calculated at 2 m resolution scored low on the predictive axis and high on the orthogonal axis \( (p_0s_o[1]) \), thereby indicating that high resolution DEMs are not suitable for TWI based soil wetness determinations.
The TPI and TLF variables both showed their best soil wetness prediction performance across the three areas when derived from the 50 m DEM, but these indices were not as good soil wetness predictors as TWI and $D_{TW}$. The flatness was a good predictor for wet areas in Area 1, but did not correspond with soil wetness determinations in Area 2 and 3. Toe-slopes, aspect, puddles, curvature and plan curvature all ranked low along the predictive horizontal axis but high on the orthogonal axis in Fig. 2, indicating that these variables are also not good soil wetness predictors.

Figure 3 illustrates the effect of scale on calculation TWI as a DEM-wetland-TWI example for Area 1 at 2, 24, and 100 m resolution. Cells with high TWI values have large contributing drainage areas and low slopes. These areas are wetlands and are displayed in blue on the map. Cells with low TWI values are well drained, dry areas and are displayed as brown on the map. The overlay of TWI on the streams and associated wetlands previously mapped at 1 : 12 500 m scale (red crosshatch) shows that TWI – when derived from the 2 m DEM – does not correspond with the wet-area distributions. However, TWI when derived from the ≥ 24 m DEMs produced good agreements for each of the three areas (Figs. 2 and 3). This is further demonstrated in Fig. 4 by the correspondence between the mapped TWI values and the field-determined soil wetness along the transect lines. The OPLS-optimum flow-initiation thresholds for $D_{TW}$-predicted soil wetness varied from 0.5 to 2 and 5 ha for Areas 1, 2 and 3, respectively (Fig. 2a–c).

Applying the $A_{CC}$ and $M_{CC}$ accuracy metrics to the $D_{TW}$-suggested wet soil locations across the combined study areas produced best-overall values of 87.1 % and 0.52 with flow-initiation thresholds of 2 and 1 ha, respectively (Table 1). By study area, the best-attained $A_{CC}$ and $M_{CC}$ values varied from 87 to 92 % and from 0.46 to 0.70. These ranges widened from 72 to 92 % and from 0.15 to 0.72 by varying the $D_{TW}$-determining flow-initiation thresholds from 0.5 to 16 ha. Across this threshold range, $A_{CC}$ and $M_{CC}$ values were more affected by study area than by resolution, with $A_{CC}$ and $M_{CC}$ generally decreasing from the 1 to the 16 ha flow-initiation threshold, while the opposite occurred for Area 3. This was also reflected by the across-area standard
deviations of the $A_{CC}$ and $M_{CC}$ estimates by flow-initiation threshold: least for 1–2 ha for Areas 1 and 2, and least for 8–16 ha for Area 3. The somewhat decreasing $A_{CC}$ and $M_{CC}$ performance for $D_{TW}$ using the flow-initiation threshold of 0.5 ha is likely due to two reasons: (i) extending the flow network to smaller and smaller reaches is directly limited by DEM resolution, (ii) with decreasing flow initiation, flow channels become drier for longer periods during each year.

Figure 5 illustrates differences between the wet areas of the Swedish property map and the $D_{TW}$ maps: many small previously unmapped wet to moist areas along the transects conformed to the latter. Specifically, $D_{TW}$ improved the $M_{CC}$ for Area 1 (Table 1, Fig. 5). For Area 2, both maps produced similar $A_{CC}$ and $M_{CC}$ values, but the $D_{TW} < 1$ m criterion did not fully capture the extent of wetland below the long hillslope. To some extent, this can be remediated by extending the $D_{TW}$-based wetland delineations towards $D_{TW} > 1$ m. For Area 3, the transect across the valley, $D_{TW}$ improved $A_{CC}$ slightly, but improved $M_{CC}$ strongly. Generally, $M_{CC}$ is better measure of model performance than $A_{CC}$ (Girard and Cohn, 2011).

4 Discussion

This study showed that the wet areas can be identified and mapped by way of DEM – derived data layers. The generally close agreement between the field-determined locations of wet soils and their corresponding TWI and $D_{TW}$ values generally confirm the underlying assumptions that water movements across the study areas are driven by gravity and that topography controls the resulting water pathways. For the boreal forest landscape, these assumptions are generally consistent with delineating the enduring soil drainage and wetland distributions (Rodhe and Seibert, 1999).

For the TWI determinations, several methods of calculating flow accumulation exist, from the simple D8 algorithm (O’Callaghan and Mark, 1984) to the more complex MD∞ (Seibert and McGlynn, 2007). Here, we used Tarboton’s D∞ method (Tarboton, 1997) since Sørensen (2006) showed that this method gave the best results for predicting...
soil wetness. Which particular TWI numbers indicate wet soils, however, vary by landscape, climate, and scale (Zinko et al., 2005; Western et al., 1999; Grabs et al., 2009; Güntner et al., 2004). The DEM scale is particularly problematic for the TWI-affecting slope derivation: with coarse DEM grids, flow channels and local depressions are not properly delineated; with fine DEM grids, local TWI variations are too strong to separate wetlands from uplands (Sørensen and Seibert, 2007). Figures 2 and 3 demonstrate that the scale as to which the TWI slope should be calculated depends on the landscape: in Area 1 and 3, the terrain was undulating and a 24 m DEM gave the best results. For Area 2, the 50 m DEM TWI derivation gave the best results along the hill slope. Since the best TWI derivations require DEM smoothing for all three areas (Fig. 3), TWI is not the best method for mapping small scale variations of wet areas along wetlands, streams and lakes.

In contrast to TWI, $D_{TW}$-based soil wetness mapping does not require DEM smoothing, and the amount of detail so revealed is mainly limited by DEM accuracy and resolution (Murphy et al., 2011, 2009, 2007). Figure 2 demonstrates that the $D_{TW}$-based wet area delineations are in fact less sensitive to the “scale” of the calculations and can therefore be considered a more robust method of predicting the wet soils. In this study the validation data set was recorded by studying the vegetation, which should reflect the average or median moisture condition of the site. By varying the flow initiation threshold, temporal variability of the stream network and adjacent wet soils can also be modelled, with lower and larger threshold values set for wet and dry seasons, respectively. For example, a 4 ha flow-initiation threshold was used to emulate end-of-summer flow and soil wetness, and soil drainage in general. Lowering this threshold to 1 and 0.25 ha would emulate soil wetness during wet summer weather and the snowmelt season (Murphy et al., 2011). $D_{TW}$ maps based on 1–2 ha flow initiation thresholds were found to work best for (i) planning or locating road-stream channel crossings except for sandy landforms such as, e.g., floodplains and glacial outwash (Campbell et al., 2013), and (ii) for estimating the distribution of wet-area obligatory species (Hiltz et al., 2012; White et al., 2012).
In detail, setting an appropriate flow-initiation threshold for the DEM-derived flow accumulation pattern depends, in part, (i) on the surface expressions of the landscape or landform as these vary from hummocky to flat, and (ii) on substrate permeabilities as these vary from high to low (Jutras and Arp, 2011, 2013). In terms of the undulating terrain covered by compacted glacial till about 5–10 m deep in Areas 1 and 2 (Seibert et al., 2009), saturated hydraulic conductivities would decrease rapidly with depth (Nyberg et al., 2001), as is mostly the case on till deposits across Scandinavia (Nyberg, 1995; Beven and Germann, 2013). As a result, (i) 90% of lateral water movements on compacted tills would occur within the top 50 cm (Bishop et al., 2011), and (ii) the soil portions of these till deposits of the area would saturate quickly during wet weather and wet seasons. Hence, subsurface flow would remain shallow and converge quickly into down-slope flow channels, each with low flow accumulation requirements. In Area 3, the terrain has high hydraulic conductivities (Koch et al., 2011), since it cuts across ice-river alluvium, mostly composed of sand, gravel and boulders, and the adjacent slopes are generally dissected by steep and deep ravines. Here, (i) water would drain quickly and deeply (Aneblom and Persson, 1979), (ii) more flow accumulation drainage area would be required for water to re-appear within the surface channels, and (iii) only the areas immediately next to the water-filled channels would remain wet. As a result, \( D_{TW} \) maps with flow-initiation thresholds from 8 to 16 ha were the most accurate for this area (Table 1).

Many of the transect-determined wet areas along streams and more diffuse areas along valley bottoms of this case study were not marked on Sweden’s current property map. But, with the \( D_{TW} \) methodology, these areas could be mapped (Fig. 5) with an overall mapping improvement for Areas 1 and 3 (Table 1). For Area 2, the \( D_{TW} < 1 \) m criterion would need to be extended to \( D_{TW} > 1 \) m to capture all of the wetland areas. In some cases, using a flatness index (e.g., White et al. (2012): mean elevational standard deviation < 0.1 m within 30 m neighborhood of each grid cell) can also be used to extend the \( D_{TW} \)-located wetland areas towards the actual wetland borders. For the Swedish context, however, large wetlands are already well mapped, but using current
maps in combination with $D_{TW}$ as in Fig. 5 improves the high-resolution delineation of all the smaller wet areas next to streams and lakes.

It is suggested that the $D_{TW}$ derived soil wetness maps can be used to reduce environmentally and economically costly off-road traffic surprises such as unacceptable rutting. For example, a recent $D_{TW}$ advance dealt with mapping potential and actual soil disturbance impacts for the purpose of off-road soil trafficability assessment (Campbell et al., 2013). Additional forestry benefits refer to improving harvest scheduling (summer vs. fall vs. winter), in-field harvest navigation, selecting tree seedlings by species for planting dry vs. moist and wet sites, and optimizing block access routes and within block harvesting and wood forwarding trails (Arp, 2009). Elsewhere, $D_{TW}$-generated data layers proved useful in systematic wetland border delineations and wetland classification (Murphy et al., 2007; White et al., 2012). Similarly, $D_{TW}$ derived maps could be useful to forecast upslope soil wetness once streams are blocked by, e.g., roads, trails, beaver dams, and logs falling across streams. In terms of vegetation indexing, Hiltz et al. (2011) was able to relate a plot-based indexing of vegetation by soil moisture regime preference to $\log_{10}(D_{TW})$. To that effect, Zinko et al. (2005) and Kunglerova et al. (2014) found a strong relationship between plant species richness, groundwater levels and local groundwater discharge areas.

5 Concluding remarks

$D_{TW}$ and TWI are both good predictors of soil wetness. However, in terms of application across Sweden, best TWI soil wetness delineations are sensitive to scale and landscape variations, and are limited in providing soil wetness detail at less than the optimal resolution of 24 m. In contrast, $D_{TW}$ is fairly scale-independent in predicting wet areas, and especially so at fine resolution. In addition, $D_{TW}$ can be further optimized by accounting for landform and substrate permeability to achieve a consistent wet-area delineation accuracy of about $A_{CC} = 80 \%$ and $M_{CC} = 0.40$. However, more research needs to be done to confirm this generalization, since till deposits, eskers and clay soils have different hydraulic conductivities. This affects the choice of setting the $D_{TW}$
determining threshold for stream-flow initiation in particular, and for water movement through watersheds in general. Selecting the optimal values for these thresholds by landform type would enable a systematical reduction of false positive and false negative wet-area determinations. In conclusion, $D_{TW}$ maps have the potential to form the next generation of high resolution wet-area maps, and the process of doing that would find many applications pertaining to forest operations planning and elsewhere.

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Table 1. Accuracy ($A_{CC}$, %) and Matthews correlation coefficient ($M_{CC}$) calculated for Areas 1, 2 and 3 by $D_{TW}$ determining flow-initiation threshold, also showing the averages and standard deviations across the areas and the flow-initiation thresholds. The best results are highlighted in bold. For comparison, numbers for the Swedish Property map (1 : 12 500) are also given.

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<th>0.5 ha</th>
<th>1 ha</th>
<th>2 ha</th>
<th>2.5 ha</th>
<th>4 ha</th>
<th>5 ha</th>
<th>8 ha</th>
<th>10 ha</th>
<th>16 ha</th>
<th>Average</th>
<th>St. Dev.</th>
<th>Map (1 : 12 500)</th>
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<td>85.9</td>
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<td>81.3</td>
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Fig. 1. Locator map for Areas 1, 2, and 3 with the Krycklan catchment with its quaternary deposits. The black lines show the location of the study transects.
Fig. 2. OPLS loading plots for Area 1, 2 and 3 and their DEM-derived terrain indices regarding soil wetness prediction. $pq[1]$ is the predictive axis and $p_0s_0$ [1] is the orthogonal (non-predictive) axis. Variables that have a high/low variable influence on the projection (VIP) are marked by black/grey text, respectively.
Fig. 3. The left panels show the hillshaded DEM in different resolutions. Topographic wetness index (TWI, right) derived from the 2, 24, and 100 m DEMs (left, hill-shaded), for a part of Area 1. Also shown on the right: lakes, streams and wetlands (crosshatched, red), previously mapped at 1:12 500.
Fig. 4. Soil wetness transects (colored lines) for Areas 1, 2 and 3 on top of the 24 m DEM-derived TWI maps (left panel). The hill-shaded 2 m DEM is overlain by the cartographic depth-to-water ($D_{TW}$) classes ranging from 0 (dark blue) to 1 m (light blue), with flow channels mapped using a 1 ha flow initiation threshold (right panel). The lower panels show close-ups for Areas 1 (1 ha flow-initiation) and Area 3 (10 ha flow-initiation).
Fig. 5. Field-mapped soil wetness superimposed on today's most high resolution map (Property map 1 : 12 500). The wet areas of the Swedish Property Map are marked in beige (left) and are superimposed by the $D_{TW} < 1$ m map (right; 1 ha flow initiation).