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ARTICLE

Comparison of Flow Direction Algorithms in the Application of the CTI for Mapping Wetlands in Minnesota

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Abstract Topography has been traditionally used as a surrogate to model spatial patterns of water distribution and variation of hydrological conditions. In this study, we investigated the use of light detection and ranging (lidar) data to derive two Single Flow Direction (SFD) and five Multiple Flow Direction (MFD) algorithms in the application of the compound topographic index (CTI) for mapping wetlands. The CTI is defined here as ln [(α)/(tan (β)], where α represents the local upslope contributing area and β represents the local slope gradient. We evaluated the following flow direction algorithms: D8, Rho8, DEMON, D-∞ MD-∞, Mass Flux, and FD8 in three ecoregions in Minnesota. Numerous studies have found that MFD algorithms better represent the spatial distribution of water compared to SFD algorithms. CTI maps were compared to field collected and image interpreted reference data using traditional remote sensing accuracy estimators. Overall accuracy results for the majority of CTI based algorithms were in the range of 81–92 %, with low errors of wetland omission. The results of this study provide evidence that 1) wetlands can be accurately identified using a lidar derived CTI, and 2) MFD algorithms should be preferred over SFD algorithms in most cases for mapping wetlands.

Keywords Wetland mapping · Lidar · Flow direction algorithm · Compound topographic index

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Introduction

Wetlands are distinctive ecosystems as a result of their hydrologic conditions, chemistry, and transitional bridge between terrestrial and aquatic life.

Wetlands benefit human society and nature in numerous ways. These include support of wildlife habitat, fishing activities and educational activities, protection of shorelines, reduction of negative effects of floods and drought, recharge of groundwater aquifers, cleansing of contaminated waters and climate regulation. The prairie pothole region of southern and western Minnesota, for example, is one of the critical waterfowl nesting and stopover points in the United States. Peatlands, which are abundant in northern Minnesota, have the ability to regulate climate change through carbon sequestration. Peatlands may hold up to 540 gigatons of carbon, representing in approximately 1.5 % of the total estimated global carbon storage (Bridgham et al. 2008; Anteau and Afton 2009; Charman 2009).

Despite their benefits, many wetlands have not been protected but instead have been drained and filled for agricultural or urban development. For example, the United States has lost about 53 % of the original wetlands since the mid-1800s. Those wetlands were converted to agricultural, urban and other commercial land uses (Dahl and Johnson 1991; Stedman and Dahl 2008). Similar change was seen in the state of Minnesota from the 1780s to the mid-1980s where about 42 % of the original wetlands were drained, ditched, filled and converted to other land uses (Dahl 2006). The vast majority of wetland loss occurred in the southern and western agricultural regions of the state while the northern forest region retains more than 90 % of its wetlands (Prince 2008).

Currently the most widely used quantitative source of wetland inventory in the majority of the United States, including Minnesota, is the National Wetlands Inventory (NWI).

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However, many NWI maps are outdated, having been completed in the late 1980's, and many changes in the landscape have occurred. Furthermore, the NWI maps were created from aerial imagery (some black and white) collected from 1979 to1988 (LMIC 2007). Thus, it is important and necessary to update wetland inventories with accurate locations of wetlands. An updated wetland inventory would greatly assist local and state government units in making better decisions for the preservation, protection and restoration of these valuable ecosystems.

The use of topography data provides a fast and cost-effective way to analyze watershed morphology, spatial distribution of soil moisture, and computation of terrain indices useful for improving river, lake, and wetland identification (Rodhe and Seibert 1999; Chaplot and Walter 2003; Sørensen et al. 2006; Corcoran et al. 2011). Digital Elevation Models (DEMs) are preferred to calculate terrain attributes because of the visual representation of these features and the easy computer implementation of algorithms to calculate terrain features (Guntner et al. 2004; Sørensen and Seibert 2007; Shoutis et al. 2010; Knight et al. 2013).

For example, flow direction algorithms can be calculated directly from DEMs to determine in which direction the outflow from a given cell will be distributed to one or more neighboring downslope cells. Flow direction algorithms are important for the calculation of topographic indices such as the Compound Topographic Index (CTI), also known as the Topographic Wetness Index (TWI). One of the valuable benefits of using indices such as the CTI is the ability to represent the distribution and flow of water (saturated vs. non-saturated areas) based only on topographic data (Moore et al. 1993; Guntner et al. 2004; Grabs et al. 2009). The CTI can identify parts of the landscape where sufficient wetness could allow the formation of wetlands. A potential issue with surface flow algorithms is that they do not detect wet areas that are not formed in topographic depressions such as groundwater discharge zones which often occur on slopes. These hydrologic settings may be more difficult to detect with flow direction algorithms in the application of the CTI for mapping rarer wetland types such as fens.

The CTI is based on the formula proposed by Beven and Kirkby (1979): CTI=ln [(α)/(tan (β)], where represents the local upslope contributing area per unit contour draining through each cell, and β represents the local slope gradient. Upslope contributing areas are calculated using a flow direction algorithm; thus, the choice of flow direction algorithm is important because it influences the spatial pattern of the CTI values.

Flow direction algorithms are divided in two main groups based on how they distribute flow from one grid cell to another cell (Erskine et al. 2006; Gruber and Peckham 2008; Wilson et al. 2008). The first group consists of single flow direction (SFD) algorithms, which allow flow to pass to only one neighboring cell downslope. The following algorithms are examples of the SFD group: the Deterministic D8 algorithm proposed by O'Callaghan and Mark (1984), and the random single direction algorithm Rho8 described by Fairfield and Leymarie (1991).

The second group consists of multiple flow direction (MFD) algorithms, which allow flow to pass to more than one neighbor cell downslope. This group is further subdivided into algorithms that allow flow to be distributed to a maximum of two, three, four, and eight neighbor cells downslope. Examples of algorithms that allow flow to be distributed to a maximum of two cells include the Digital Elevation Model Network (DEMON) proposed by Costa-Cabral and Burges (1994), and the Deterministic Infinite (D ∞) algorithm suggested by Tarboton (1997).

The Mass Flux (MF) algorithm proposed by Gruber and Peckham (2008) is an example of algorithms that allow flow to pass into a maximum of four neighbors cells. Examples of algorithms that allow flow to be distributed to a maximum of eight neighbor cells include the Triangular Multiple Flow direction algorithm (MD ∞) proposed by Seibert and McGlynn (2007), and the Divergent Flow algorithm (FD8) proposed by Freeman (1991). Studies related to hydrological applications across disciplines have used SFD algorithms such as the D-8 more often than MFD algorithms. Although several studies have confirmed that MFD algorithms can provide more accurate results in calculating the distribution and flow of water, the use of SFD algorithms continues (Wilson and Gallant 2000; Zhou and Liu 2002; Pan et al. 2004).

Numerous studies have shown differences between SFD and MFD algorithms for stream network applications and statistical distribution of primary and secondary terrain attributes (Tarboton 1997; Guntner et al. 2004). However, little research has been done to assess the accuracy of these types of algorithms using high resolution elevation data in the application of topographic derivatives such as CTI for identifying wetlands in the upper Midwest, U.S.A. In recent years, the acquisition of high resolution elevation data using Light Detection and Ranging (lidar) has increased.

Lidar is an active remote sensing technology that uses laser light to produce accurate land elevation data. Numerous studies have confirmed the importance of lidar data to improve the process of mapping wetlands (Jenkins and Frazier 2010; Knight et al. 2013; Lang et al. 2013). Lang and McCarty (2009) mapped forested wetlands using lidar intensity and obtained a high overall acccury of 96.3 %. They compared their lidar intensity results to NIR photointerpretation of wetlands, which had an overall accuracy of 70 % for the same area. Antonarakis et al. (2008) also achieved high overall accuracy results of 95–99 % for mapping open water features using a combination of lidar intensity and lidar derived terrain attributes. Thus, the goal of this paper was to assess the suitability of a selection of two Single Flow Direction (SFD) and five Multiple Flow Direction (MFD) algorithms for use in creating several CTIs from lidar data for wetland mapping in three ecoregions in the state of Minnesota, U.S.

Study Areas Description

This study was conducted in three study areas within three different ecoregions in the state of Minnesota (Fig. 1). The first study area is located in the Northern Glaciated Plains ecoregion and consists of five watersheds of a 12-digit-level Hydrologic Unit Code (i.e., HUC-12). The five watersheds include Big Stone Lake, Big Stone Lake State Park, Barry Lake, Fish Creek, and Salmonson Point, all within Big Stone County. The total area of the five watersheds together is 293 km^2 with primarily loamy soils and a mixture of well and poorly drained soils. Land use within these watersheds is predominantly agricultural with grain crops, including corn and soybeans. The elevation of these watersheds ranges from 290 to 364 m above sea level.

The average annual precipitation in this area is 640 mm with 360 mm occurring in the growing season of May to September. These watersheds are part of the prairie pothole region in Minnesota, characterized by numerous small depressional wetlands known as prairie potholes. Wetlands in this ecoregion are of vital importance for waterfowl habitat, storage of surface water, groundwater recharge and discharge, and reduction in the risk of downstream flooding (Winter and Rosenberry 1995; LaBaugh et al. 1998).

The second study area is located in the Central Hardwood Forest ecoregion and contains five watersheds of a 12-digit level Hydrologic Unit Code (i.e., HUC-12). The five watersheds include Upper Lake Minnetonka, Riley Creek, Purgatory Creek, Lower Lake Minnetonka and the City of Shakopee-Minnesota River. These watersheds are located within Hennepin and Carver counties. The total area of the five watersheds is 69 km^2, with fine to moderately coarse texture and well drained soils. Land use is dominated by urban development including medium density residential, with some areas for commercial growth and open space. The elevation across these watersheds is 209–332 m above sea level. The average annual precipitation is 762 mm while during the growing season (May to September) it is 508 mm. The majority of the wetlands types in these watersheds are shallow marshes and wet meadows (City of Chanhassen Surface Water Management Plan 2006).

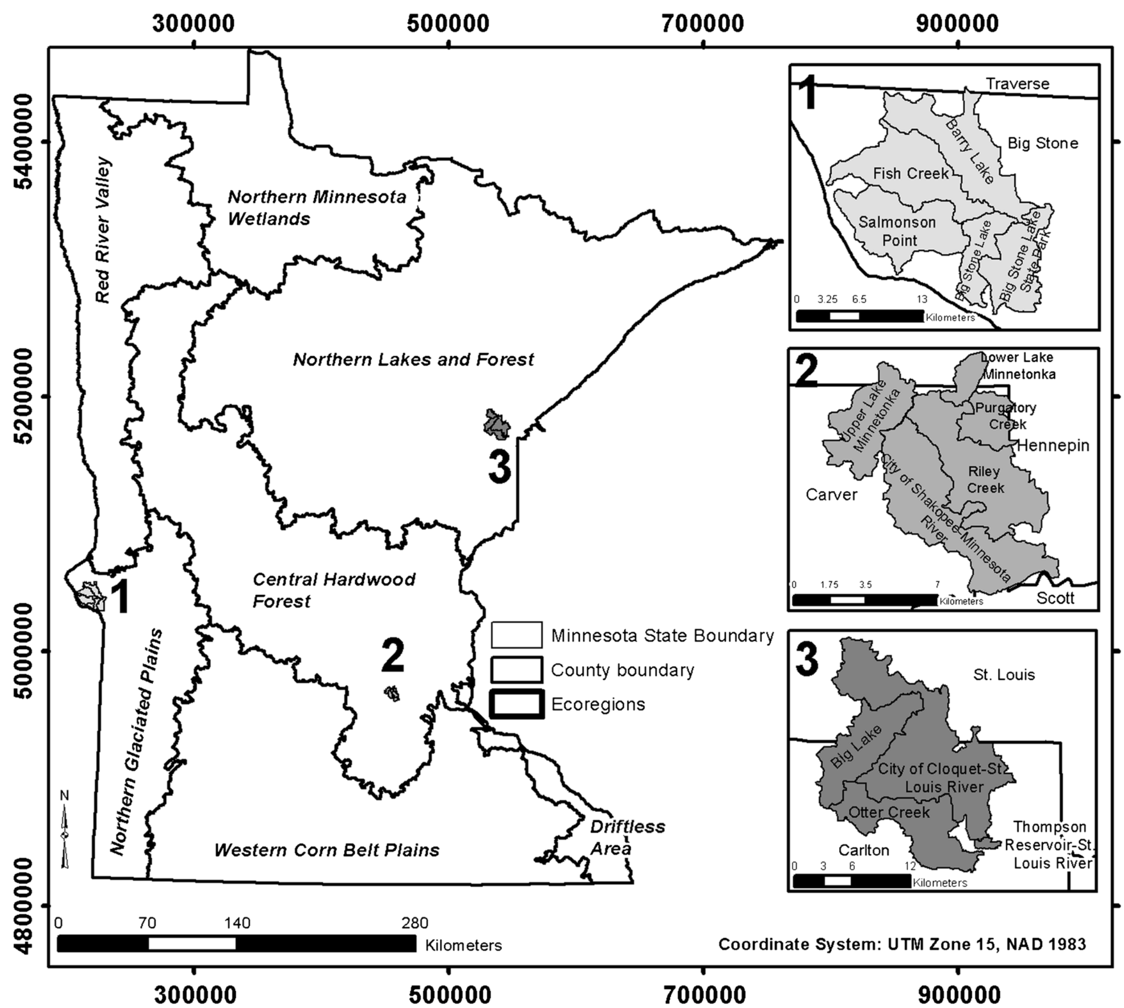

Fig. 1 Three study areas located in three different ecoregions in the state of Minnesota, U.S.A

The third study area is located within the Northern Lakes and Forest ecoregion and includes four watersheds of a 12-digit level Hydrologic Unit Code (i.e., HUC-12). The four watersheds include Big Lake, the City of Cloquet-St. Louis River, Otter Creek and the Thompson Reservoir-St. Louis River. These watersheds are located between St. Louis and Carlton counties. The total area of the four watersheds together is 265 km^2 with poorly drained soils and near-surface water tables. The main land use in these watersheds is mixed forested land dominated by conifer forest, mixed hardwood-conifer forest and conifer bogs and swamps. The elevation in these areas ranges between 307 and 436 m above sea level. The average annual precipitation is 710 mm and during the growing season (May to September) the average precipitation is 440 mm. Wetlands types in these watersheds are primarily forested wetlands covered by coniferous and tall shrubby vegetation (Minnesota Department of Natural Resources 2010).

Lidar Data

We used a 3 m lidar DEM for each study area to compute seven different flow direction algorithms. The 3 m lidar DEM for the Northern Glaciated Plains study area was obtained from the International Water Institute (IWI) lidar download portal. The DEM was created by interpolating the bare earth point LAS files using the 'Raster to ASCII' command in the Environmental Systems Research Institute (ESRI) ArcGIS software.

Collection of the lidar data used to create the DEM occurred during the spring of 2010 (leaf-off conditions) by Fugro Horizons Inc. with an average post spacing of 1.35 m. The lidar data horizontal accuracy was of +/− 1 m (95 % confidence level), with a vertical accuracy RMSE of 15.0 cm.

The 3 m lidar DEM for the Central Hardwood Forest study area was downloaded from the Minnesota Geospatial Information Office (MnGeo). This lidar DEM was produced by the Minnesota DNR by extracting bare earth points from the point cloud data. The DEM was hydro flattened using the edge of the water breaklines. Collection of the lidar point cloud data took place between Nov 11 and Nov 17, 2011 by Fugro Horizons Inc. with an average post spacing of 1.5 m. The horizontal accuracy for these data was of +/− 0.6 m (95 % confidence level), and a vertical accuracy RMSE of 5 cm.

The 3 m lidar DEM for the Northern Lakes and Forest study area was also acquired from the Minnesota Geospatial Information Office (MnGeo). The 3 m DEM was produced by the Minnesota DNR by extracting bare earth points from the point cloud data. The DEM was also hydro flattened using the edge of the water breaklines. Acquisition of the lidar data took place between May 3 and May 5, 2011 by Woolpert Inc. with an average post spacing of 1.5 m. The horizontal accuracy of the lidar data was +/− 1.2 m (95 % confidence level), with a vertical accuracy RMSE of 5 cm.

Analysis Methods

This section is composed of three subsections: The first describes the pre-processing steps applied to the lidar DEMs. The second describes the steps and software used to calculate each of the lidar derived terrain attributes required for the CTI calculation CTIs. The third explains the accuracy assessment procedures used to assess the results for each study area.

Lidar DEM Pre-Processing

Each lidar DEM was subset to a shapefile watershed boundary that was obtained from the Minnesota Department of Natural Resources (DNR). Sinks or pits that did not have a surface water outlet were moderately filled to avoid irregularities that could interfere with correct hydrologic flow (trapping flow). We used the tool *fill sinks XXL* implemented in the free open source software System for Automated Geoscientific Analysis (SAGA) v. 2.1.0. We chose this tool because it offers the option to fill sinks fully or partially by keeping a minimum slope gradient along the flow path.

Otherwise, if no minimum slope gradient value was specified, all the sinks would be filled to the spill elevation which would create completely flat areas. Due to the high resolution of our lidar DEMs we avoided filling surface depressions completely by preserving a minimum slope gradient of 0.001 between cells. The resultant sink-moderately-filled DEM for each study area was used to compute the required terrain attributes for calculation of the upslope contributing areas.

Derived Terrain Surfaces

The following flow direction algorithms were implemented in different software packages for the computation of seven upslope contributing areas: The D8, Rho8 and DEMON algorithms were implemented using the SAGA software; the FD8 and MD-∞ algorithms were implemented using Whitebox Geospatial Analysis Tools v. 1.0.7 open source software; the Mass Flux algorithm was implemented using the River Tools v. 3.0.3, GIS software; the D∞ algorithm was implemented using the Terrain Analysis Using Digital Elevation Models (TAUDEM) v. 5.0 toolbox in ArcGIS 9.3.1; and the seven upslope contributing areas for each study area were used to calculate the seven CTIs in ArcGIS v. 10.1.

We computed a slope grid in degrees from the partially prefilled DEM using the spatial analyst tool in ArcGIS v. 10.1 and then converted to radians using the raster calculator. The method used in ArcGIS to compute the slope is the average maximum technique, where the maximum rate of change in value from a cell to its neighbors is calculated using a 3×3 cell neighborhood around the center grid cell (Burrough and McDonell 1998).

We modified the resultant slope by adding a minimum value of 0.0001 to avoid division by zero for CTI calculations. The raster calculator in ArcGIS v. 10.1 was used to modify the slope and impose the minimum value. Finally, we calculated all the CTIs based on the formula proposed by Beven and Kirkby (1979): CTI=ln [(α)/(tan (β)]. The CTI computations were carried out in ArcGIS v. 10.1 using the raster calculator from the Spatial Analyst toolbox.

Accuracy Assessment

We evaluated the CTI results for each study area based on traditional accuracy assessment methods, including error matrices, overall accuracy, producer's accuracy, user's accuracy, and kappa statistic (k-hat) for upland and wetland classes. We also executed a significance test of error matrices known as the Z Pair-Wise statistical test described by Congalton and Green (2009). This Z-test was used to determine whether there was a statistically significant difference between the various CTIs at an alpha level of 0.05. The Z-test was also performed between every CTI and the NWI wetland map using the same classification scheme (upland/wetland).

We thresholded the CTI results into two classes: uplands and wetlands. The threshold values were determined through a series of trial-and-error experiments, where several CTIs across the three different ecoregions were assessed against field data collection and photointerpretation reference points. Results indicated that the most common value for separating upland from wetlands using a 3 m lidar CTI was always the value closest to the mean value of the entire range.

The CTIs and NWI were assessed against a set of independent randomly generated sample points for each study area. These reference data used for the Northern Glaciated Plain and Central Hardwood Forest study areas were collected from a few sources that included: randomly generated field sites visited by trained field crews in the summers of 2009 and 2010, plots generated by the MN Department of Natural Resources Wetland Status and Trend Monitoring Program (WSTMP) using centroids from polygons of 2006 and 2008 updates, and randomly generated points using photointerpretation by our experienced analyst.

The reference data used for the Central Hardwood Forest study area was developed by the City of Chanhassen using a combination of photo-interpretation and field data collection during the fall of 2004, and the growing season of 2005. The field data collected for the three study areas contained the following information: Plant type and percent coverage, land-cover/land-use type, UTM coordinates, 5–6 photos per site, and the Cowardin wetland type (Cowardin et al. 1974). Upland types included crop fields, other agriculture, forests, grasslands, urban areas, construction areas, bare areas, and others. We used 2000 reference data points for the Northern Glaciated Plains study area, 9,994 for the Central Hardwood Forest study area and 2,000 for the Northern Lakes and Forest study area.

Results

Accuracy assessment results and significance tests of the three study areas are summarized in Tables 1, 2, 3, 4, 5, and 6. Maps of the seven CTIs and NWI wetland/upland classification are displayed in Figs. 2, 3, 4, 5, 6, and 7. Overall accuracy results for the majority of CTIs across the three study areas were in the range of 81–92 % with low errors of wetland omission.

Wetlands larger than 0.20 ha (0.5 acres) throughout the three study areas were identified by all the algorithms, with producer's and user's accuracies in the range of 67–97 % and 65–98 %, respectively.

Table 1 Accuracy estimators of the seven CTIs algorithms and the NWI for the Northern Glaciated Plains study area (Classification scheme: wetland/upland)

CTI algorithm	Threshold used	Overall accuracy	Wetland user's accuracy	Upland user's accuracy	Wetland producer's accuracy	Upland producer's accuracy	Overall kappa
D8	6.0	92	87	98	97	87	0.84
Rho8	6.7	71	70	72	67	75	0.42
DEMON	8.1	92	87	97	96	88	0.84
D-∞	7.2	92	87	97	97	87	0.84
MD-∞	6.1	92	87	97	97	87	0.83
Mass Flux	6.1	91	98	85	85	98	0.82
FD8	11.0	86	87	85	82	89	0.71
NWI	1	88	87	89	87	88	0.76

Total # points used for the accuracy assessment: 2000

Table 2 Significance test (Z-test) for comparing the seven algorithms and the NWI for the Northern Glaciated Plains study area (Classification scheme: wetland/upland)

CTI type	Kappa1 vs. Kappa2	*Z*-value
D8 vs. Rho8	0.84 vs. 0.42	17.6*
D8 vs. FD8	0.84 vs. 0.71	6.7*
D8 vs. NWI	0.84 vs. 0.76	4.5*
Rho8 vs. DEMON	0.42 vs. 0.83	17.5*
Rho8 vs. D-∞	0.42 vs. 0.84	17.6*
Rho8 vs. MD-∞	0.42 vs. 0.83	17.2*
Rho8 vs. Mass Flux	0.42 vs. 0.82	16.6*
Rho8 vs. FD8	0.42 vs. 0.71	10.9*
Rho8 vs. NWI	0.42 vs. 0.76	13.2*
DEMON vs. FD8	0.83 vs. 0.71	6.5*
DEMON vs. NWI	0.83 vs. 0.76	4.3*
D-∞ vs. FD8	0.84 vs. 0.71	6.6*
D-∞ vs. NWI	0.84 vs. 0.76	4.4*
MD-∞ vs. FD8	0.83 vs. 0.71	6.2*
MD-∞ vs. NWI	0.83 vs. 0.76	4.0*
Mass Flux vs. FD8	0.82 vs. 0.71	5.6*
Mass Flux vs. NWI	0.82 vs. 0.76	3.4*
Fd8 vs. NWI	0.71 vs. 0.76	2.24*

*A *Z*-value over 1.96 indicates that there is a significant difference at the 95 % confidence level

Also, a comparison assessment of the seven CTIs and the original NWI was performed for each study area, using the same two classes (wetland/upland). The comparison assessment was done using the kappa-statistic (Z- test) proposed by Congalton and Green (2009). The majority of the CTIs based flow direction algorithms derived from lidar data for identifying wetlands; produced higher accuracy results compared to the NWI results that were in the range of 75–88 % for overall accuracy, 73–97 % for user's accuracy and 71–87 % for producer's accuracy across the three study areas.

Results for the Northern Glaciated Plains Study Area

Detailed accuracy assessment results of the seven CTIs algorithms and NWI results of two classes (wetland/upland) are reported in Table 1. The overall accuracies for the CTIs evaluated in this area were in the range of 71–92 %, with overall kappa scores in the range of 0.42–0.84. Producer's and user's accuracies for the CTI's were in the range of 67–97 % and 70–98 % respectively.

The majority of CTIs, with the exception of the CTI Rho8, showed low errors of commission and omissions for the wetland class. The NWI accuracy assessment results were lower than the majority of CTIs for predicting wetland locations in this study area. Table 2 displays only the significance test (Z-test) results of those CTI and NWI results that were found to be statistically different at a 95 % confidence level. These Z-test results revealed that the CTI FD8, CTI Rho8 and NWI maps were significantly different compared to every CTI evaluated.

This statistical difference for the CTI FD8, CTI Rho8 and NWI suggests that the other algorithms are more suitable for identifying wetland occurrences in this ecoregion.

A visual comparison of the seven CTI algorithms and NWI polygons for a small portion of the Northern Glaciated Plains study area are presented on Fig. 2.

This qualitative comparison revealed more details of the differences between the algorithms and the original NWI polygons for representing flow water distribution in wetlands in that area. Figure 3 illustrates a Color-Infrared (CIR) map and a CTI map for this entire study area. Overall, the D8, D-∞, and Mass Flux CTIs were the only algorithms for this study area that showed excellent agreement with the reference data in the visual and quantitative assessment, with the highest overall accuracy results in the range of 91–92 %.

Results for the Central Hardwood Forest Study Area

Accuracy assessment results of the seven CTIs algorithms and NWI results of two classes (wetland/upland) for this study area are presented in Table 3.

Table 3 Accuracy estimators of the seven CTIs algorithms and the NWI for the Central Hardwood Forest study area (Classification scheme: wetland/upland)

CTI algorithm	Threshold used	Overall accuracy	Wetland user's accuracy	Upland user's accuracy	Wetland producer's accuracy	Upland producer's accuracy	Overall kappa
D8	6.1	88	88	89	89	87	0.77
Rho8	5.5	72	71	74	75	70	0.45
DEMON	7.3	85	85	85	85	85	0.71
D-∞	5.4	86	82	92	93	79	0.72
MD-∞	5.1	87	87	87	87	87	0.74
Mass Flux	5.0	85	84	87	87	84	0.71
FD8	5.6	70	70	70	71	70	0.41
NWI	1	85	97	77	71	98	0.70

Total # points used for the accuracy assessment: 9994

Table 4 Significance test (Z-test) for comparing the seven algorithms and the NWI for the Central Hardwood Forest study area (Classification scheme: wetland/upland)

CTI type	Kappa1 vs. Kappa2	*Z*-value
D8 vs. Rho8	0.77 vs. 0.45	28.7*
D8 vs. DEMON	0.77 vs. 0.71	6.21*
D8 vs. D-∞	0.77 vs. 0.72	4.7*
D8 vs. MD-∞	0.77 vs. 0.74	2.9*
D8 vs. Mass Flux	0.77 vs. 0.71	6.0*
D8 vs. FD8	0.77 vs. 0.41	31.9*
D8 vs. NWI	0.77 vs. 0.70	7.6
Rho8 vs. DEMON	0.45 vs. 0.71	22.5*
Rho8 vs. D-∞	0.45 vs. 0.72	24.15*
Rho8 vs. MD-∞	0.45 vs. 0.74	25.7*
Rho8 vs. Mass Flux	0.45 vs. 0.71	22.7*
Rho8 vs. FD8	0.45 vs. 0.41	3.18*
Rho8 vs. NWI	0.45 vs. 0.70	21.6*
DEMON vs. MD-∞	0.71 vs. 0.74	3.2*
DEMON vs. FD8	0.71 vs. 0.41	25.7*
D-∞ vs. FD8	0.72 vs. 0.41	27.4*
D-∞ vs. NWI	0.72 vs. 0.70	2.8*
MD-∞ vs. Mass Flux	0.74 vs. 0.71	3.0*
MD-∞ vs. FD8	0.74 vs. 0.41	28.9*
MD-∞ vs. NWI	0.74 vs. 0.70	4.5*
Mass Flux vs. FD8	0.71 vs. 0.41	25.9*
Fd8 vs. NWI	0.41 vs. 0.70	24.8*

*A *Z*-value over 1.96 indicates that there is a significant difference at the 95 % confidence level

Overall accuracy percentages for the CTIs assessed in this study area were in the range of 70–88 %, with overall kappa scores in the range of 0.41–0.77. Producer's and user's accuracies for the CTI's were in the range of 71–93 % and 70–88 %, respectively. The majority of CTI algorithms excluding the Rho8 and FD8 showed low errors of commission and omissions for the wetland class. NWI producer's accuracy was relatively low compared to the majority of CTIs, which resulted in higher rates of wetland omission in this area. Table 4 displays the significance test (Z-test) results of those CTIs and NWI maps that were found to be significantly different at a 95 % confidence level.

The CTI FD8, CTI Rho8 and CTI D8 were found to be statistically significant compared to the rest of the CTI and NWI results. A detailed visual comparison of the seven algorithms, wetland polygons created by the City of Chanhassen, and NWI polygons for a small portion of this study area is presented in Fig. 4. This visual comparison exposes many differences between the polygons created by the City of Chanhassen, the NWI polygons and the straight flow water patterns of the single flow direction algorithms. A map of the CTI and CIR image for the complete study area is shown in Fig. 5.

In general, out of all the algorithms tested, the D-∞ and MD-∞ CTIs indicated excellent agreement with the reference data in the visual and quantitative assessment for this study area. These CTIs had high overall accuracy results in the range of 86–87 %, with low errors of wetland omissions and commission.

Results for the Northern Lakes and Forest Study Area

Table 5 shows accuracy assessment results for the two classes (wetland/upland) for this study area. Overall accuracy results for the CTI's based algorithms evaluated in this study area were in the range of 69–82 % with kappa scores between 0.38 and 0.64. Producer's and user's accuracies for the CTI's were in the range of 80–86 % and 65–81 %, respectively. NWI accuracy assessment estimators were lower compared to the majority of the CTI algorithms for this area. Lower accuracy assessment results of the NWI revealed the inaccuracy of the polygons in this forested area for identifying wetlands, particularly forested wetlands.

Table 6 displays significance tests (Z-tests) for only CTI algorithms that were found to be statistically different at a

Table 5 Accuracy estimators of the seven CTIs algorithms and the NWI for the Northern Lakes and Forest study area (Classification scheme: wetland/upland)

CTI algorithm	Threshold used	Overall accuracy	Wetland user's accuracy	Upland user's accuracy	Wetland producer's accuracy	Upland producer's accuracy	Overall kappa
D8	5.2	82	80	84	86	78	0.64
Rho8	6.1	69	65	77	84	54	0.38
DEMON	7.1	75	73	77	80	70	0.50
D-∞	7.0	81	81	81	81	81	0.61
MD-∞	5.5	82	80	83	84	80	0.63
Mass Flux	6.0	81	80	81	82	79	0.61
FD8	5.8	81	79	83	83	78	0.61
NWI	1	75	73	78	80	70	0.50

Total # points used for the accuracy assessment: 2000

Table 6 Significance test (Z-test) for comparing the seven algorithms and the NWI for the Northern Lakes and Forest study area (Classification scheme: wetland/upland)

type	Kappa1 vs. Kappa2	*Z*-value
D8 vs. Rho8	0.64 vs. 0.38	9.78*
D8 vs. DEMON	0.64 vs. 0.50	5.43*
D8 vs. NWI	0.64 vs. 0.50	5.24*
Rho8 vs. DEMON	0.38 vs. 0.50	4.18*
Rho8 vs. D-∞	0.38 vs. 0.61	8.84*
Rho8 vs. MD-∞	0.38 vs. 0.63	9.43*
Rho8 vs. Mass Flux	0.38 vs. 0.61	8.59*
Rho8 vs. FD8	0.38 vs. 0.61	8.80*
Rho8 vs. NWI	0.38 vs. 0.50	4.37*
DEMON vs. D-∞	0.50 vs. 0.61	4.52*
DEMON vs. MD-∞	0.50 vs. 0.63	5.10*
DEMON vs. Mass Flux	0.50 vs. 0.61	4.28*
DEMON vs. FD8	0.50 vs. 0.61	4.48*
D-∞ vs. NWI	0.61 vs. 0.50	4.34*
MD-∞ vs. NWI	0.63 vs. 0.50	4.91*
Mass Flux vs. NWI	0.61 vs. 0.50	4.10*
Fd8 vs. NWI	0.61 vs. 0.50	4.30*

*A *Z*-value over 1.96 indicates that there is a significant difference at the 95 % confidence level

95 % confidence level. The CTI FD8, CTI Rho8 and CTI D8 were found to be statistically significant different compared to the rest of the CTI and NWI results for mapping wetlands. Visual comparisons of the seven CTI algorithms and NWI polygons for a small portion of this study area are shown in Fig. 6. This visual comparison revealed the differences between the algorithms and NWI polygons for predicting forested wetlands. Figure 7 shows two maps: the CTI and CIR image, for the whole study area. In general, the D-∞, MD-∞, and Mass Flux CTIs were the only algorithms that had excellent agreement with the reference data in the visual and quantitative assessment for this study area. These three algorithms had the highest overall accuracy results in the range of 81–82 %, with relatively low errors of wetland omissions and commission.

Discussion

We compared and evaluated seven CTI based algorithms derived from lidar DEMs for identifying wetlands across three different ecoregions in Minnesota. The computation of the CTI offered a practical and fast method to identify wetlands greater than 0.20 ha. All CTI based maps showed a relatively high overall percentage of agreement with the reference data for wetland and upland classes (69–92 %). Results of this study demonstrate that lidar derived CTIs can significantly improve the accuracy of wetlands classification compared to the NWI across different ecoregions in Minnesota.

Although a direct comparison of the NWI and our CTI results may be not fair because of the differences in data types and techniques used to create these two wetland maps; the CTI-based approach developed here provides an alternative efficient and accurate method to update wetland maps. Available updated wetland maps would be valuable for many governmental and non-governmental entities that currently only used NWI maps as a tool and resource to monitor and take decisions regarding wetlands.

Our results showed the importance of choosing the correct flow direction algorithm for identifying wetlands location visually and quantitatively. Visual comparison of the seven CTI algorithms in the three study areas revealed noticeable differences that are partially seen in the quantitative accuracy assessment analysis for some algorithms.

We speculate that the quantitative accuracy assessment analysis did not show strong differences for all the algorithms because of the type of reference data used to assess these algorithms: points instead of polygon reference data types. For example, the D8 SFD algorithm exhibits similar quantitative accuracy results compared to three of the MFD algorithms (D-∞, MD-∞, Mass Flux) in the three study areas; nevertheless, the qualitative visual analysis exposes major difference related to unrealistic parallel flow patterns of the SFD algorithms (D8 and Rho8) for differentiating wetlands from uplands.

Similarities and differences between the two groups of algorithms are also highlighted in the way each of these algorithms tends to distribute the flow and accumulation of water in wetlands and uplands across the three study areas.

The Northern Glaciated Plains study area exhibited similarities in the way the majority of the CTI based algorithms represented water flow and accumulation for wetland mapping. For example, the D8, D-∞, and Mass Flux CTIs showed parallel flow patterns and similarly high accuracy assessment results. Low topography relief and presence of more concave hillslopes in this study area were the two main factors that favored greater flow convergence for the majority of wetlands located in this study area. These factors may explain the similarities in performance of the majority of flow direction algorithms in this area. Additionally, this study area had the highest overall accuracy, user's and producer's accuracy results compared to the other two study areas.

High accuracy results can be explained primarily because of the type of wetlands found in this study area, known as prairie pothole wetlands or depressional wetlands (LaBaugh et al. 1998). The majority of flow accumulation that contributes to the hydrology of these wetlands tends to occurs in these topographic depressions that can be identified efficiently using high resolution elevation data. As a result, the CTI method tested in this

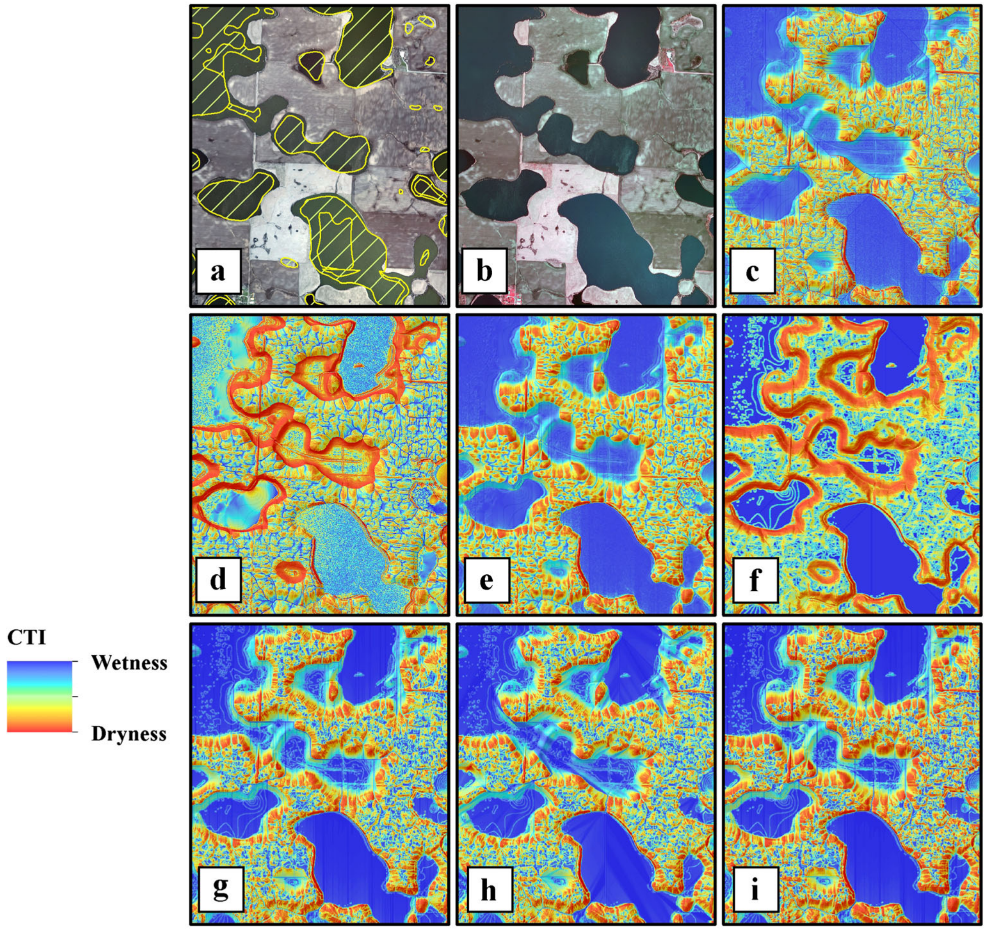

Fig. 2 Visual comparison of **a** the NWI polygons, **b** CIR aerial imagery 2011, **c** D8 CTI, **d** Rho8 CTI, **e** DEMON CTI, **f** FD8 CTI, **g** D-∞ CTI, **h** MD-∞ CTI, **i** Mass Flux CTI for the Northern Glaciated Plains study area. Higher CTI values represent water accumulation (potential wetland location) and lower CTI values represent dryness

study is an efficient mapping technique to identify these wetlands because of the topographic nature of this index.

For the Central Hardwood Forest study area marked visual differences between the SFD and MFD algorithms were

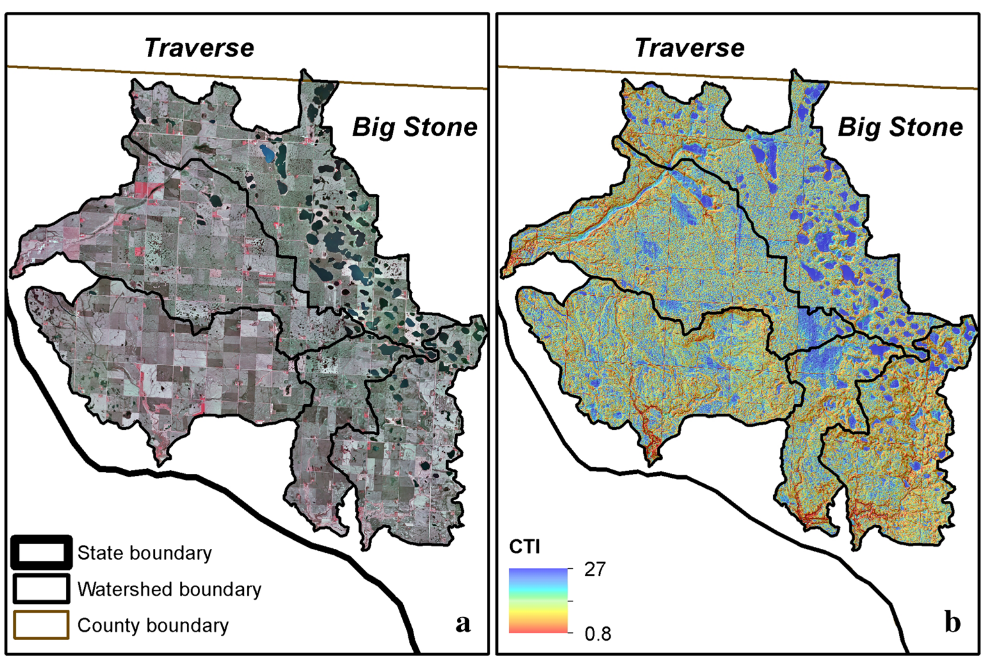

Fig. 3 **a** CIR aerial imagery 2011 map, and **b** CTI map for the Northern Glaciated Plains study area

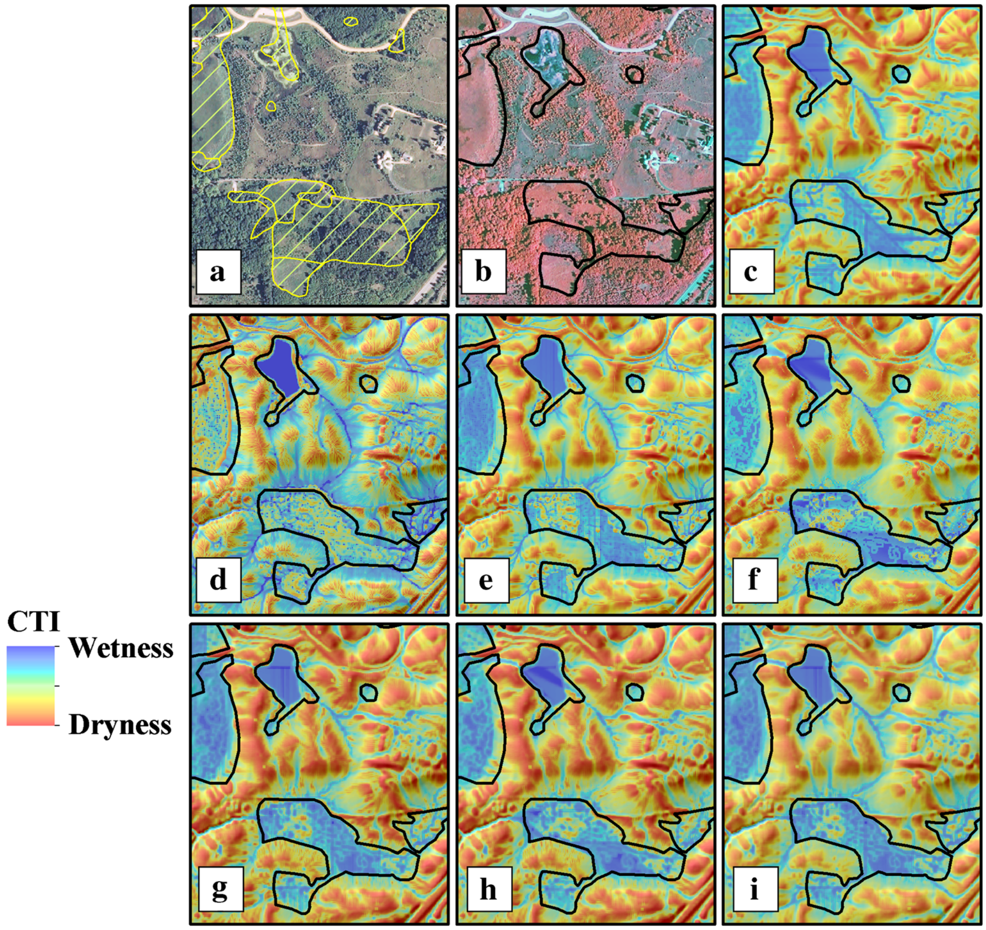

Fig. 4 Visual comparison of **a** the NWI polygons, **b** CIR aerial imagery 2008 and wetland polygons created by the City of Chanhassen, **c** D8 CTI, **d** Rho8 CTI, **e** DEMON CTI, **f** FD8 CTI, **g** D-∞ CTI, **h** MD-∞ CTI, **i** Mass Flux CTI for the Central Hardwood Forest study area. Higher CTI values represent water accumulation (potential wetland location) and lower CTI values represent dryness

displayed in this study. For example, parallel flow patterns were very evident on the D8, Rho8 and DEMON CTIs. The Rho8 showed the lowest accuracy assessment results for classifying wetlands and uplands.

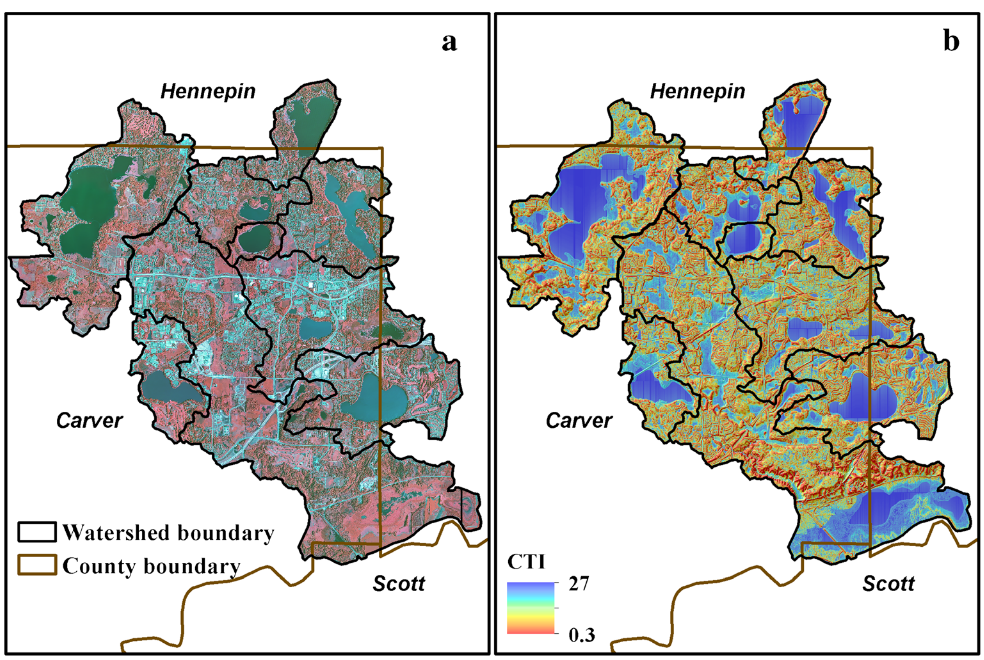

Fig. 5 **a** CIR aerial imagery 2008 map, and **b** CTI map for the Central Hardwood Forest study area

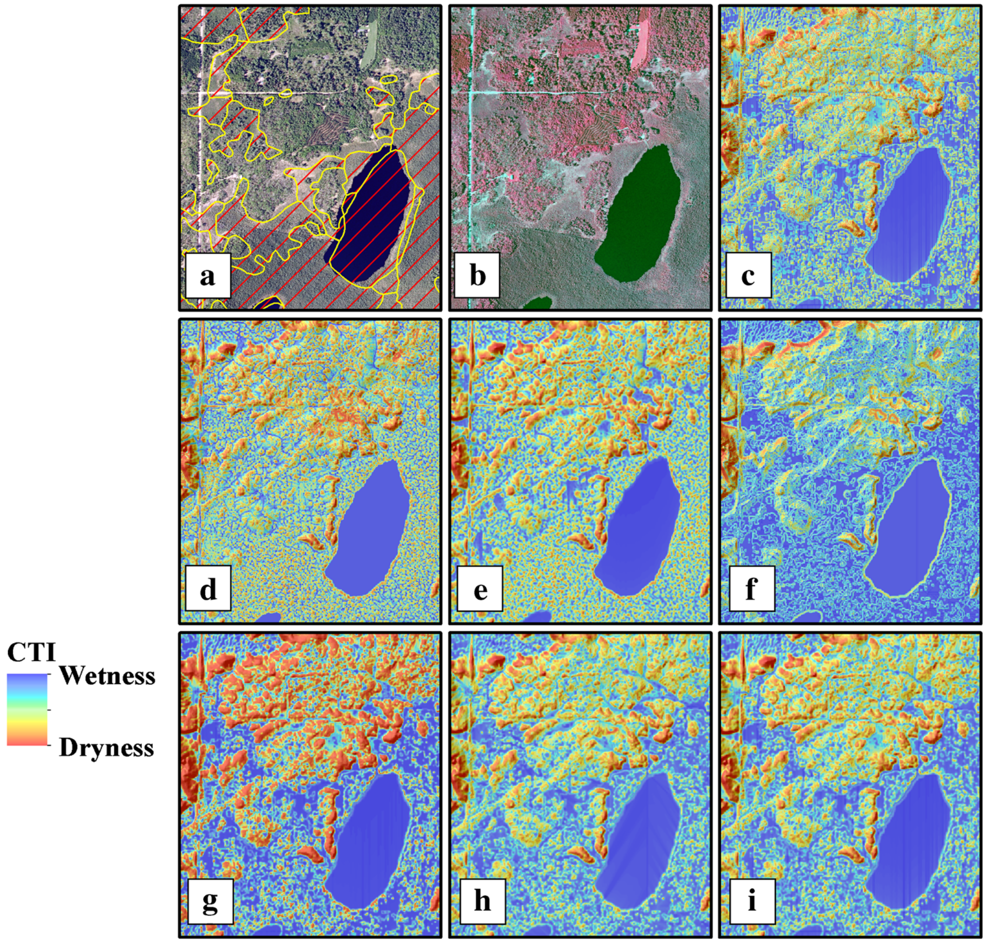

Fig. 6 Visual comparison of **a** the NWI polygons, **b** CIR aerial imagery 2009 , **c** D8 CTI, **d** Rho8 CTI, **e** DEMON CTI, **f** FD8 CTI, **g** D-∞ CTI, **h** MD-∞ CTI, **i** Mass Flux CTI for the Northern Lakes and Forest study area. Higher CTI values represent water accumulation (potential wetland location) and lower CTI values represent dryness

This study area had the second relatively high overall accuracy, user's and producer's accuracy results compared to the other two study areas. Visually and statistically the best algorithms for mapping wetlands in this area were the D-∞ and MD-∞ CTIs. Marked differences between algorithms in this study area can be attributed to the presence of medium to

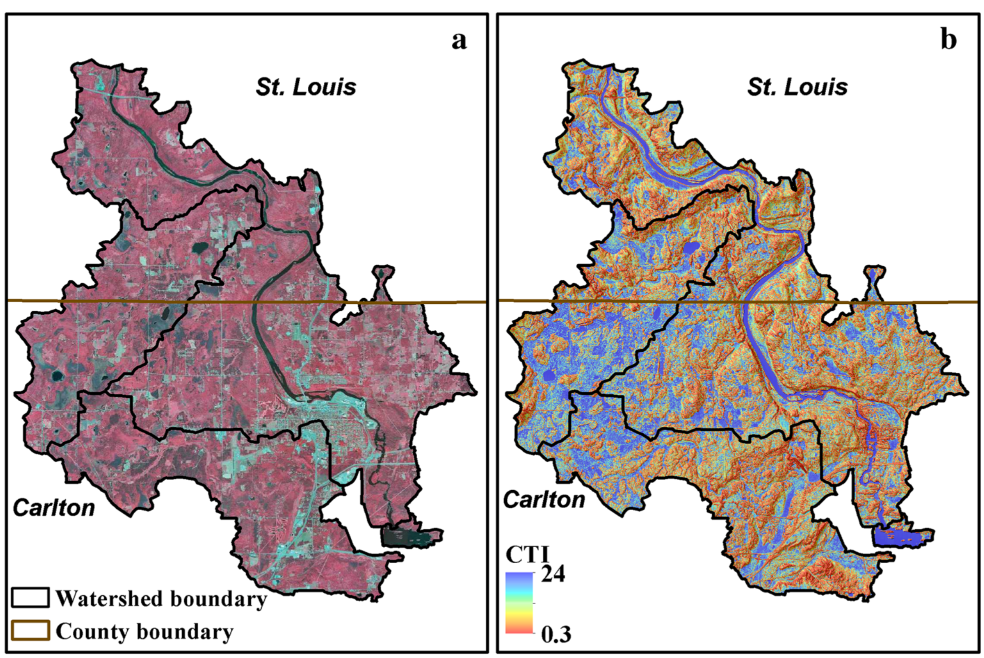

Fig. 7 **a** CIR aerial imagery 2009 map, and **b** CTI map for the Northern Lakes and Forest study area

high topography relief and more convex hillslopes near or in the type of existing wetlands in this area.

The majority of existing wetlands include open water, shallow and deep marshes, and unconsolidated bottom (Knight et al. 2013). Thus, CTIs based on MFD algorithms were more suitable than SFD algorithm for this area to represent realistic patterns of wetlands areas and greater flow of divergence distribution of water.

The Northern Lakes and Forest study area study area had the lowest overall accuracy, user's accuracy, and producer's accuracy results for all the CTIs maps compared to the other two study areas. This can be explained because of the wetlands types located in this area which includes calcareous fens, sedge meadows, hardwood wetlands, coniferous swamps, and coniferous bogs. The majority of these existing wetlands in this area are groundwater-fed wetlands, and generally high in the landscape.

For example, fens wetlands are groundwater discharge wetlands that occur along topographic or geologic breaks or where groundwater aquifers are exposed near the surface. Thus, these types of wetlands are less sensitive to topography influence and inundation events as they are located at an elevation above floodplain.

Nevertheless, of all the CTI's based algorithms, the MFD algorithms performed better at visually separating uplands from wetlands. The D-∞, MD-∞, and Mass Flux CTIs had the highest accuracy results for separating wetlands from uplands. The three MFD algorithms mentioned above allowed for a more divergent and smoother distribution of water in very pronounced convex-steep hillslopes near or close to these wetlands.

Lang et al. (2013) reinforces our results regarding the accuracy and preferences for MFD over SFD algorithms for identifying wetland locations. The Lang et al. (2013) results indicate that the FD8 CTI multiple flow direction algorithms derived from lidar data performed better than other non-distributed flow direction algorithms including the D8 for identifying locations of forested wetlands in the Coastal Plain of Maryland.

Our significance Z-test results for the three study areas confirmed the significant differences between the SFD algorithms and MFD, particularly for the Rho8 CTI, across the three study areas. CTI based algorithms (D8, D-∞, MD-∞, Mass Flux D, and FD8) wetland/upland classification maps in general were significant improvements over the NWI map for two of our study areas. However, for the Central Hardwood Forest study area, the CTI based algorithms (D8, D-∞, MD-∞, and Mass Flux D) outperformed only the NWI. NWI results in this area had high errors of omission because of rapid urban development over the past 6 years.

Our research demonstrated the outdated nature of many NWI maps in Minnesota. Still, many of these maps are used by governmental and non-governmental policymakers for wetland management and policy development for lack of better data. Improved mapping accuracy will be greatly beneficial for policymakers developing local or regional wetland inventories, restoration or mitigation plans and other policies.

Conclusions

Lidar derived CTIs enable a fast, efficient, and more accurate method to estimate current wetland location compared to NWI maps. Our results provide evidence that different wetland types in varied ecoregions can be identified accurately using lidar derived terrain indices. In general, the seven CTI based algorithms were able to predict wetland locations across different ecoregions. However, there were statistically and visually significant differences in their performance.

Our visual comparison results revealed that CTIs based on MFD algorithms are generally better than CTIs based on SFD algorithms for separating wetlands from uplands. Based on our results, we suggest the use of the following algorithms: D-∞, MD-∞ or Mass Flux in the application of the CTI for mapping wetlands in areas similar to the ones evaluated in this study. The MFD algorithms represented the distribution and accumulation of water (wetness) in wetlands in a more visually accurate form compared to SFD algorithms.

Further research is encouraged to investigate the effect of different DEM resolutions and use of the CTI combined with other ancillary data such as optical data for mapping wetlands. The combination of the CTI and other ancillary data could potentially help to identify wetlands located at an elevation above floodplain level where elevation information alone is not as influential as it is for depressional wetlands. For example, organic flat wetlands and groundwater discharge-fed wetlands that occur along slopes including some types of fens may require additional tools to map with greater accuracy.

Additional research is also needed to address evaluate numerically the visual differences seen in this study from the different flow direction algorithms. One possible approach could be a wet area-polygon based assessment, that would extract and measure the amount of CTI wet areas found only in wetland references polygons.

Finally, the use of NWI maps continues across different parts of the country because these maps are the most accessible information available. Many of these NWI maps need to be updated. Remote sensing techniques including those based on the CTI offer a fast, cost-effective and reliable method to quickly identify wetland location and update such maps.

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