New mapping techniques to estimate the preferential loss of small wetlands on prairie landscapes

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Abstract:
Reliable estimates of wetland loss require improved wetland inventories and effective monitoring programmes. The Prairie Pothole Region of North America is experiencing rapid urban, agricultural and economic development, which places wetlands at risk, especially small geographically isolated wetlands. This loss is concomitant with a loss of ecosystem services. To improve upon current wetland inventories, a method for mapping wetlands using an automated object-based approach was developed for a regional watershed in Alberta. The method improves upon existing wetland mapping methods by effectively mapping small wetlands and better capturing the convolution of wetland edges. This approach uses digital terrain objects derived from light detection and ranging data, from which 130 157 wetlands were identified. Wetland loss estimates (% number and % area) were obtained by applying a wetland area versus frequency power-law function to the wetland inventory. We estimated a 16.2% historic loss of wetland number and a 2.6% loss of wetland area, with the size of these lost wetlands <0.04 ha. The improved techniques for mapping wetland loss and estimating wetland loss provide a more accurate representation of the magnitude of wetland loss in the Prairie Pothole Region. Copyright © 2015 John Wiley & Sons, Ltd.

KEY WORDS mapping techniques; wetland; wetland loss; power-law; area; frequency

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INTRODUCTION

The Prairie Pothole Region is a large physiographic region extending from the Prairie Provinces of Canada into the Northern Great Plains of the USA. This unique landscape is due to the deposition of glacial till and the forces of melting ice and glacial scouring during the last glacial period (Kantrud et al., 1989). Glacial retreat left the landscape pockmarked with millions of small typically disconnected depressions or ‘potholes’. These potholes are isolated from the surface water network, and thus are known as geographically isolated wetlands (Tiner, 2003). It is estimated that up to 70% of wetlands have been lost or degraded in areas near the Canada–US border (Warner and Asada, 2006). These losses are attributed to increasing urban and agricultural development pressures causing wetlands to be dredged and drained for the purposes of economic expansion (Davidson, 2014). In the US portion of the Prairie Pothole Region, 95% of the loss of wetlands to uplands from 1997–2009 occurred as a result of agricultural development (Dahl, 2014).

When these wetlands are lost, associated functions are lost as well (Naugle et al., 2001; Zedler and Kercher, 2005). A common misconception about prairie potholes is that the lack of surface water and connectivity to the surface water network indicates that these wetlands function less than more permanent wetlands and therefore provide fewer ecosystem services (e.g. Semlitsch and Bodie, 1998; McLaughlin et al., 2014). Although prairie potholes are disconnected from the surface water network, they have been found to have important contributions to the groundwater system via wetland-groundwater interactions and can be either groundwater sinks or sources (McLaughlin et al., 2014). In addition, prairie potholes are considered important biogeochemical reactors within watersheds as they remove nutrients such as nitrogen (Crumpton and Goldsborough, 1998; Lane et al., 2015) and phosphorus (Reddy et al., 1999; Craft and Casey, 2000; Dunne et al., 2007) and sequester carbon (Badiou et al., 2011; Creed et al., 2013) at rates comparable with or higher than connected wetlands. Prairie potholes provide ecosystem services such as the desynchronization and attenuation of floodwater before it enters the surface water network (Lane and D’Amico, 2010; Pomeroy et al., 2014) and the improvement of downstream water quality (Westbrook et al., 2011).

Wetlands need to be managed effectively in a manner that balances the needs for economic development and the preservation of ecological services provided by wetlands.
Successful wetland management requires accurate wetland inventories to estimate rates of change in wetland number and area and to understand the spatial and temporal patterns of these changes (Li and Chen, 2005). Unfortunately, current wetland inventories are often incomplete, time-consuming to create, non-standardized and out of date (Baker et al., 2006). National wetland data exist for both Canada [Canadian Wetland Inventory (CWI)] and the USA [National Wetland Inventory (NWI)]. However, the size of the minimum mapping unit (MMU) for these inventories ranges from 0.02 (manually derived) to 1 ha for the CWI (Fournier et al., 2007) and from 0.4–1.2 ha for the NWI (Martin et al., 2012). These current wetland inventories are too coarse in resolution to be useful in the Prairie Pothole Region (Finlayson et al., 1999; Clare and Creed, 2013; Na et al., 2013; Davidson, 2014) where the majority of prairie potholes are smaller than 1 ha (van der Valk and Pederson, 2003). It is difficult to effectively manage and obtain estimates of the loss of small wetlands when all wetlands are not captured (Na et al., 2013). Small (<1 ha) wetlands are vulnerable to continued loss on prairie landscapes, in part because they are often not included in wetland inventories.

Wetland managers need high-resolution wetland mapping techniques that are sensitive to the detection of small wetlands and simple standardized methods to estimate the loss of all sizes of wetlands. Several challenges exist when creating accurate and automated wetland inventories, including the lack of techniques to capture their size and shape because wetlands on prairie landscapes often hold water for only short periods of time, such as after the spring melt or during summer storms (Tiner, 2003). The complexity of the edges of isolated wetland basins is often difficult to capture in wetland inventories because of coarse resolution data inputs and dynamic water levels. Edges are frequently under-estimated or over-estimated when wetlands are digitized manually. It is important to capture the shape of wetland boundaries as wetland morphometry affects wetland function. For example, the convolutedness of an isolated wetland’s edges can be an indicator of the ability of a wetland to process nutrients (e.g. denitrify) (Marton et al., 2015). The small area, transient nature and dynamic open water boundary make these wetlands difficult to map and particularly vulnerable to anthropogenic loss.

Another challenge is the lack or inadequacy of wetland monitoring programmes to estimate the magnitude and rate of loss. To effectively estimate wetland loss over time, we need historic inventories or information to serve as a benchmark; however, these data often do not exist. Further, there is no standardized approach for estimating wetland loss (Dahl and Watmough, 2007). One approach to estimating wetland loss is to combine historic wetland inventories (e.g. NWI data) and current land cover data. A change in a historically mapped wetland to urban land cover denotes loss (e.g. Johnston, 2013). Several studies in Canada (Watmough and Schmoll, 2007) and the USA (Johnston, 2013; Dahl, 2014) have used a combination of historic aerial photographs, multi-spectral imagery and plot/transect studies to estimate historic changes in wetlands over time. However, these methods are time-consuming and prone to error due to the quality of the data sources used or human error (Davidson, 2014).

The purpose of this paper is to present new techniques that overcome these challenges. The first objective is to present a technique for mapping wetlands that is particularly sensitive to mapping the small (<1 ha) wetlands that dominate the prairie pothole landscape. The second objective is to use this wetland inventory to estimate historic loss of these wetlands. The resulting wetland inventory will allow for better management of wetlands and for better understanding and monitoring of wetland losses.

METHODS

Test area

The Beaverhill watershed (4500 km²) is located in Central Alberta and covers a portion of the Prairie Pothole Region (700,000 km²) of North America (Figure 1).

The climate is continental with an average annual temperature of 2.6 °C characterized by warm summers and cold winters and a total average annual precipitation of 446.1 mm, with the majority of the precipitation falling during the growing season (April–October) (Environment Canada, 2010). Precipitation minus potential evapotranspiration (Hamon, 1961) for the watershed is typically negative, with a few periods of moisture availability experienced during the growing season (Figure 2). The landscape is a rolling, hummocky terrain that was created because of glaciation. Elevation within the watershed ranges from 586–812 m above sea level. The landscape is pockmarked with a large number of depressions that fill up with water either temporarily in the spring or have a surface water connection, which allows them to contain water permanently all year round. Soil types within the study area include primarily Black Chernozemic, Black Solonetzic and Orthic Grey Luvisols, and the bedrock is composed of sandstone, siltstone, mudstone, shale and ironsite beds (Howitt, 1988). The natural vegetation within the watershed is characteristic of the Parkland natural region of Alberta and the Central Parkland and Central Mixwood natural sub-regions of Alberta, including a mixture of aspen and prairie vegetation dominated by plains rough fescue (Festuca hallii (Vasey) Piper) and aspen trees (Populus tremuloides Michx.) (Natural Regions Committee, 2006). Climate oscillations between dry and wet periods are common (Figure 2) (Duvick and
Blasing, 1981), and there are north–south temperature and east–west precipitation gradients within the Prairie Pothole Region that contribute to the varying wetland hydrologic characteristics throughout the Prairie Pothole Region (Johnson et al., 2005). The small size and transient nature of the hydrologic regime of the wetlands makes them sensitive to changes in the amount of precipitation and evaporation, and thus climate change.

Land uses within the watershed are representative of Southern Alberta, ranging from urban to agricultural (predominantly grassland and pastureland) to natural forests. Development pressures within the watershed have been primarily attributed to the conversion of land to cattle pasture and croplands (Young et al., 2006). Urban expansion has occurred around the City of Edmonton and Strathcona County, but the rate of expansion is estimated to be slower than the expansion experienced in other areas of Southern Alberta (e.g., Calgary) (Clare and Creed, 2013). Future urban land use change is expected to occur within the watershed as the City of Edmonton is projected to expand at an estimated rate of 1.3%/year from 2006 until 2041 (Government of Alberta, 2007).

Figure 1. Map showing the location of the study watershed, the Beaverhill watershed, Alberta, Canada. The location of the validation and calibration sites is shown
**Wetland inventory**

We used multiple datasets from various sources to map wetlands within the study area (Table I). The MMU is the minimum area of a wetland that can be reliably mapped using a given wetland mapping method. The MMU varies for each individual wetland mapping method and is dependent upon the resolution of the input data, any known errors in the data and the method used to map wetlands. We used the high-resolution, manually delineated portion of the CWI derived from aerial photography (MMU = 0.02 ha) to calibrate and validate our automatic object-based wetland inventory derived from a light detection and ranging (LiDAR) digital elevation model (DEM). The data used for the manually derived wetland inventory (collected in 2007) and our object-based wetland inventory (2009) were collected within 2 years of each other, and we assumed there was no significant wetland loss from 2007–2009.

**Manually delineated wetlands.** Within certain areas of the Canadian portion of the Prairie Pothole Region, there is a high-resolution wetland inventory that was created by Ducks Unlimited Canada (2014) and is part of the CWI. This manually derived high-resolution wetland inventory covered a large portion of the study area but did not include any urban areas. The high-resolution wetland inventory was created from stereo-pairs derived from 1:20,000 aerial photographs that were captured during the growing season of 2007 (Figure 3). Original negatives of the images were scanned on a photogrammetric scanner to a pixel resolution of 25 cm. Stereo-models were then created using existing ground control points, and elevation data were obtained from a hydrologically enhanced DEM. To delineate wetland boundaries, stereo interpretation was used to identify geomorphic and vegetative indicators of a wetland’s presence, and the boundaries of the wetlands were captured manually using this information. Individual wetland features were mapped according to the National Wetlands Data Model (Natural Resources Canada, 2010) and classified according to the Canadian Wetland Classification System (National Wetlands Working Group, 1997). To meet the needs of our study, the boundaries of the individual wetland features were dissolved to create wetland objects. Wetlands classified as dugouts or human-made features were removed from the reference data as the focus of this study was on natural wetlands.

**Automatically delineated wetlands.** A strong association exists between depressions on the landscape, defined as low-lying areas that are completely surrounded by higher elevation, and wetland occurrence (e.g. Creed et al., 2003). A LiDAR DEM with a horizontal resolution of 3 m and an estimated vertical accuracy of 15 cm was used to develop a probability of depression (p_{dep}) layer that forms the foundation of the wetland mapping technique. The majority of LiDAR data were captured during the months of June–November of 2009 [a small amount of LiDAR captured during the Fall (August–November) of 2007 and 2008 was filled where required] during a period with large moisture deficits, reducing the amount of standing water on the landscape.

The p_{dep} layer was developed using the Monte Carlo method of Lindsay et al. (2004). Random elevation errors

### Table I. List of data layers used in this project. Where the minimum mapping unit (MMU) was not provided, a minimum resolvable unit (MRU) was calculated by using the method by Tobler (1987)

<table>
<thead>
<tr>
<th>Data layer</th>
<th>Resolution</th>
<th>MRU/MMU (ha)</th>
<th>Source data years</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital elevation model</td>
<td>3 m</td>
<td>MRU = 0.0009</td>
<td>2009</td>
<td>Airborne Imaging Inc.</td>
</tr>
<tr>
<td>Canadian Wetland Inventory</td>
<td>1 : 20000</td>
<td>MMU = 0.02</td>
<td>2007</td>
<td>Ducks Unlimited</td>
</tr>
<tr>
<td>National Road Network</td>
<td>1 : 50000</td>
<td>MRU = 0.25</td>
<td>2009</td>
<td>Statistics Canada</td>
</tr>
</tbody>
</table>

Figure 2. The Beaverhill Lake water level and precipitation-potential evapotranspiration (P-PET) (growing season) for the Beaverhill watershed from 1900–2010.
were added to the bare earth LiDAR DEM with a standard deviation equal to the DEM’s vertical accuracy of 0.15 m. Depressions in the DEM were filled using the Wang and Liu (2006) algorithm, and after the filling, modified cells were identified and recorded. This process was repeated until a stable solution was reached, meaning that the root mean square difference between two realizations was less than 0.001, with a maximum of 1000 iterations. The probability of depression was then calculated by the number of times a cell was recorded as having been filled divided by the number of iterations. A value of 0 in the p_{dep} layer means that the cell was not filled during any of the simulations and therefore has no probability of being a depression; a value of 1 indicates that the cell was filled in every simulation and therefore has a 100% probability of being a depression (Creed and Beall, 2009).

The resulting p_{dep} layer was segmented into terrain objects following the multi-resolution segmentation algorithm (Baatz and Schäpe, 2000) using eCognition Developer (v 8.0). By conducting object-based segmentation on the probability of depression layer, we were able to improve representation of wetland boundaries and capture a broad range of wetland size. The multi-resolution segmentation algorithm begins with one pixel and merges similar single pixels based on a pair-wise clustering processes; this algorithm was conducted at different scales to allow for the detection of both small and large wetlands (Carleer and Wolff, 2006). The pair-wise clustering process merges regions with similar colour, smoothness, compactness to create relatively homogeneous image objects (Carleer and Wolff, 2006; Aldred and Wang, 2011). User-specified segmentation parameters such as colour, shape, compactness and scale can define and constrain the segmentation process. Shape was given no weight in the segmentation in our analysis. In addition, a high compactness criterion (0.8) was used to produce compact terrain objects. The scale parameter in object-based segmentation is a unitless value that determines the maximum possible change in heterogeneity that can be caused by merging neighbouring image segments into one segment (Ikokou and Smit, 2013). The lower the threshold, the lower the possible change in heterogeneity and thus the smaller the image segment. We used a small-scale parameter of 2 and a larger scale parameter of 20 to map wetlands. The scale parameter of 2 is typically smaller than what is used in existing wetland studies (Reif et al., 2009; Moffett and Gorelick, 2013), but it was deemed as appropriate for this study as it allowed for the detection of small wetlands that are characteristic of prairie landscapes. The larger scale parameter was required as the smaller scale parameter terrain objects, when classified, were found to miss portions of larger wetlands because of the variation in mean terrain object p_{dep} values within wetlands.

We also buffered a vector polyl ine road layer for each of the sites by 15 m on each side, including the road...
network line, to reduce the probability of misclassifying roadside ditches as wetlands. Fifteen metres was determined to be sufficient as the roadside ditches of most roads were included entirely within this buffer. This 15 m buffer layer was input as a vector layer to constrain the segmentation so that the terrain objects would not transverse roads and was also input as a binary raster layer that was used in the classification of terrain objects.

Wetland boundaries were delineated by classifying terrain objects. For mapping smaller wetlands (scale parameter = 2), the mean $p_{dep}$ value within terrain objects threshold was determined using calibration sites. We established 125 randomly distributed 1.5 x 1.5 km calibration sites (Figure 1) within the watershed based on the following criteria: (1) they were within the extent of the reference data in the watershed and (2) they did not have a large water body occupying the entire site. The selection of thresholds is important because it affects the number and size of wetlands that are classified as wetlands. For example, the selection of a low mean $p_{dep}$ value threshold results in a higher number and larger size of wetlands being delineated, whereas a higher mean $p_{dep}$ value threshold results in a lower number and smaller size of wetlands.

We applied nine different mean $p_{dep}$ thresholds to the terrain objects at 0.05 intervals ranging from 0.30–0.70. Terrain objects with a mean $p_{dep}$ value greater than or equal to the nine thresholds were classified as a wetland for each wetland map. The Pearson coefficient ($r$) and absolute difference in wetland area between the object-based wetlands and the reference wetlands were then calculated. A threshold was selected that (1) maximized the $r$ between the two images and (2) minimized the absolute magnitude of the difference in wetland area between the object-based classification and the reference data. A threshold was selected for each calibration site, and then the average threshold for all sites was calculated. For mapping larger wetlands (scale parameter = 20), the threshold for the mean $p_{dep}$ value in a terrain object to classify as a wetland was determined by iteratively assessing smaller $p_{dep}$ threshold values and comparing the results to the small scale parameter (2) results – if wetland areas that were not being classified as wetlands using the smaller scale parameter were classified as wetlands for a given threshold, then the threshold was selected for the larger scale parameter.

We merged and dissolved the results of classifying both scale parameters to form a single wetland inventory. We removed any wetland objects that had an area of less than the MMU of the reference data (0.02 ha) in both the reference data and the mapped data to conduct the accuracy assessment and ensure fair comparisons. A flow chart of the method to create the manually delineated wetlands is shown in Figure 4.

Comparison of manually derived versus automatically derived wetland inventories. To assess the accuracy of our wetland mapping method, we used the segmentation and threshold parameters that were established via the calibration process on 125 validation sites that were randomly distributed throughout the watershed. The reference data and the object-based wetland inventories were then compared – if a mapped wetland intersected a wetland within the reference data, then that wetland was present in both datasets and therefore assumed to be correct. Although this accuracy assessment method does not compare the wetland size or shape, we deemed it to be appropriate as the shape and size of wetlands can be dynamic, varying with climatic conditions, and therefore comparing wetland size and shape would likely lead to erroneous accuracy statistics because the inventories were not created at the exact same time using the exact same method and data inputs. The omission accuracy (producer accuracy) was calculated as the number of wetlands in the reference data that intersect the object-based wetland data divided by the total number of wetlands in the reference data. The commission accuracy (user accuracy) was calculated as the number of wetlands in the object-based mapped data that intersected the reference data divided by the total number of wetlands in the object-based mapped data. Wetlands that did not intersect the reference data were referred to as ‘potential’ wetlands due to the fact that, without field verification, it is difficult to determine their presence on the landscape.

We also compared centroids in the reference data and the object-based wetland inventory to further determine the accuracy of our method. Although the shape and size of wetlands between the two wetland inventories are likely not similar because of the difference in time periods captured, the centroids of the wetlands should be close to each other. To examine whether or not the centroids were close, we took all wetlands that intersected each other in the reference data and the object-based wetland inventory. The average width of the reference wetland was then calculated, and centroids for both data were created. The distance between the centroids in both data was calculated and then compared with the average width of the reference wetland. If the distance between centroids was less than the average width of the reference wetland, then the mapped wetlands in both datasets were considered to be similar.

Open water permanence. We generated an open water permanence map by applying a different object-based segmentation method to historic black and white aerial photographs and manually classifying resulting image objects for the years 1962, 1970, 1982, 1993, 1999 and 2009. The 1962, 1993 and 2009 aerial photographs were taken during the spring (April or May, with exception of a minor part of 1993 where July and August 1992 images were used to fill in gaps and 2009 where April and May 2007
images were used to fill in gaps). The aerial photographs for 1970, 1982 and 1999 were taken in the summer of their respective years (July–September), except for 48% of the 1982 aerial photograph, which was filled with summer 1981 data where required. This time series represents the varying hydrologic conditions within the watershed (Figure 2).

To conduct the object-based segmentation, we used a scale parameter of 40, due to the increased spectral heterogeneity within the aerial photographs. We used a low shape to colour ratio (0) and a compactness criterion of 0.5. We conducted overlay analysis with inventories for the 6 years, and if a portion of a wetland had water for all 6 years, it was considered to have 100% probability of water permanence.

Both the object-based wetland inventory and the reference data were overlaid onto the water permanence map to examine the hydroperiod of wetlands that were being mapped.

**Wetland loss**

A power-law function of wetland area versus wetland frequency was used to estimate historic wetland change (Miller et al., 2009; Zhang et al., 2009). The selection of the power-law function was based on the premise that water bodies are fractal (Brown et al., 2002), meaning that there is a repeating pattern of water body morphology at all scales, and thus, the frequency of the area of water bodies when plotted on logarithmic–logarithmic scales produces a straight line (negative linear relationship) in an undisturbed region (Kent and Wong, 1982). A deviation from this theoretical line reflects a loss in wetland number and area if the deviation is below the line, and a gain if the deviation is above the line. Wetland change was estimated by the difference in area between the line and the observed break in slope in the line (Figure 5). A log wetland area versus log wetland frequency plot was generated for wetlands larger than 0.02 ha in size; the bins for wetland area were equal to the resolution of the data that was used to create the wetland inventory [i.e. 0.0001 ha (1 m²)]. Piecewise linear regression analyses were performed to identify breakpoints (Seber and Lee, 2012). When conducting a piecewise linear regression, a separate regression line is fit for each
differently linear trend that occurs within the data, and breakpoints are identified between each different trend. The breakpoint indicates an abrupt change in the data and is often considered to be a critical threshold that can be used for decision-making (Vieth, 1989). First, a three-segment piecewise linear regression was performed; wetlands above the larger wetland area breakpoint were removed (the larger area breakpoint would occur at a bin with a frequency of 1, so bins with a frequency of 1 were removed from the analysis). Second, a two-segment piecewise linear regression was performed on the remaining data and a straight line was created by extrapolating a linear regression from the data above the smaller wetland area breakpoint and below the larger wetland area breakpoint. Wetland number loss was calculated as the difference between the wetland number estimated by the theoretical line and the actual wetland number observed for all area classes below the small wetland area breakpoint, and wetland area loss was calculated as the difference between the wetland area estimated by the theoretical line and the actual wetland area observed for all area classes below the small wetland area breakpoint.

RESULTS

Wetland inventory technique

Calibration of technique. The statistics used to determine thresholds in the mean p\textsubscript{dep} value within terrain objects, including the correlation coefficient and the absolute magnitude of the difference in wetland area between the manually and the object-based wetland data, were calculated using Whitebox [v3]. There was a strong downward trend with increasing p\textsubscript{dep} threshold when calculating the absolute difference in area between the reference data and the object-based wetland inventory (Figure 6a). The trend for the correlation between the two images (Figure 6b) was not as clear because of the varying response of each validation site to the probability of depression thresholds. The threshold for the small-scale parameter of 2 was calculated to be 0.52 (any terrain object that had a mean p\textsubscript{dep} value greater than 52% was classified as a wetland). The threshold for the larger scale parameter of 20 was 0.45; when this threshold was applied to the larger terrain objects, portions of the wetland that were not captured by the smaller scale parameter were captured.

Validation of technique. The omission error for all of the validation study sites for wetlands larger than 0.02 ha in size was 18%, and the commission error was 45%. The size of the wetlands that were being committed or omitted within the validation sites (potential wetlands) tended to be small in size (<0.5 ha), with a large number of the wetlands being <0.1 ha (i.e. approximately 32×32 m) (Figure 7a). Five of the validation sites were located in industrial areas on the edge of the city of Edmonton. These industrial validation sites had higher errors, with an overall omission error of 21% and overall commission error of 72%. Applying object-based segmentation to the p\textsubscript{dep} maps for the validation sites, as opposed to applying a straight pixel classification threshold to the p\textsubscript{dep} maps, decreased our commission error by 5%. Using object-based techniques to...
segment the image into two sizes of terrain objects, we were able to decrease the omission error by 4%. The application of object-based techniques to the \( p_{\text{dep}} \) maps increased the detection of wetlands on the landscape.

Analysis of the distance between wetland centroids in the reference data and the object-based wetland inventory yielded an average distance of +6.4 m between the centroids of all intersecting wetlands. When the difference between the average width of the reference wetland and the distance between the two centroids was calculated, it was found that 74.3% of the mapped wetlands had centroids that were separated by a distance that was less than the average width of the reference wetland, indicating a large amount of overlap between the two wetland polygons in both datasets.

**Wetland inventory**

A larger number of potential wetlands <1 ha in area were mapped than the reference data (Figure 7b, c). Within the validation sites, the wetland mapping technique identified 5276 wetlands and potential wetlands larger than 0.02 ha, with a total area of 2749.41 ha. The average area of these wetlands was 0.52 ha (range = 0.02–63.33 ha; median = 0.089 ha), in comparison with the 1 ha average area of wetlands within the reference data. For the entire watershed, 130 157 wetlands (including potential wetlands) larger than 0.02 ha were identified, with a total area of 111 167 ha. The average wetland size for the entire watershed was 0.85 ha (range = 0.02–19 040.19 ha; median = 0.09 ha). The object-based wetland inventory mapped 63% more wetlands and 39% more wetland area than the reference data for the Beaverhill watershed, where the reference data included the manually derived wetland inventory plus System Pour L’Observation Terre (SPOT) imagery derived wetlands for areas (about 60% of the watershed) not covered by the manually derived wetland inventory. The SPOT imagery was collected in 2006 and 2008 and is 10 m in resolution. Wetlands were mapped using multi-spectral classification methods.

We used the perimeter-to-area ratio as an indicator of the convolutedness of the wetland boundary. The object-based wetland inventory suggested that wetland boundaries were more convoluted than the reference data, with the average PA ratio being 0.22 for the object-based wetland inventory, compared with 0.15 for the CWI for wetlands greater than 0.02 ha in both inventories. In addition to capturing the increased convolution of wetland edges, the object-based method was able to automatically detect hydrological connections among wetlands because of the high-resolution nature of the LiDAR DEM. These hydrologically connected wetlands appeared as individual wetlands in the reference data; however, when an aerial photograph was underlain under the wetland inventory, surface hydrologic connections (e.g. rivers or streams) between the CWI wetlands were observed in the aerial photographs (Figure 8). When the water permanence layer was underlain on the object-based wetland inventory, it indicated that the object-based method accurately detected wetlands with 100% probability of open water, but also detected wetlands that were transiently filled with water. The higher number and area of wetlands detected using the object-based method tended to be transient wetlands (Figure 9).

**DISCUSSION**

The Prairie Pothole Region of North America contains millions of depressional wetlands. The small and shallow nature of these wetlands allows for quick conversion of wetlands to agriculture (Galatowitsch and van der Valk, 1996). To better manage these important ecosystems, improved estimates of wetland location and loss are needed to allow decision makers to balance economic and development needs while maintaining the important functions and ecosystem services wetlands provide (Zedler and Kercher, 2005).
Early methods for the creation of wetland inventories involved visual interpretation of aerial photographs or satellite imagery to delineate wetland boundaries (Hutton and Dincer, 1981). This visual analysis of images is effective at providing wetland location (Johnston and Barson, 1993); however, these methods are labour intensive and prone to error. Automated delineation methods using high-resolution data and remote sensing techniques are being developed to overcome the limitations of manual delineation. Currently, automated wetland inventory methods use digital elevation (Na et al., 2013), multi-spectral (Baker et al., 2006; Frohn et al., 2012), optical (Li and Chen, 2005; Haas et al., 2009) and/or microwave (Gala and Melesse, 2012; Allen et al., 2013) remotely sensed data.

There are problems with these advances in automated wetland mapping methods. Often, the remotely sensed imagery is low resolution, sometimes up to 30 m. These low-resolution data result in a greater proportion of mixed pixels in topographically complex landscapes minimizing detection of wetlands <30x30 m. Further, the use of satellite imagery alone to map wetlands may produce

Figure 8. The 2009 aerial photograph underlying the object-based wetlands (blue boundary). The hydrologic connections seen on the aerial photograph are highlighted.

Figure 9. Wetlands (grey hatching) mapped by the automated object-based method with the water permanence layer providing information about wetland permanence.
inaccurate results because of spectral similarities between different types of vegetation (Ozesmi and Bauer, 2002; Maxa and Bolstad, 2009). The accuracy of these automated wetland-mapping techniques improves when ancillary data are considered. For example, Maxa and Bolstad (2009) used high-resolution LiDAR data and IKONOS imagery to map wetlands. They manually captured wetland boundaries using a fusion of the two images and found that using a combination of LiDAR and IKONOS was 18.5% more accurate than the Wisconsin Wetland Inventory maps for the same region (Maxa and Bolstad, 2009). Lang et al. (2012) developed topographic indices from a LiDAR DEM and compared them with existing inundation and wetland maps. They found that a hybrid of topographic indices (e.g. topographic wetness indices and relief information) provided a good indication of wetland location and inundation period and that the resulting maps using the hybrid topographic indicators were similar to existing aerial photograph-derived wetland maps. These studies indicate that topographic information, such as those derived from LiDAR DEMs, can assist in mapping wetlands.

The automated wetland mapping technique developed in this study, based on terrain objects derived from LiDAR DEMs, was effective at mapping wetlands and sensitive to capturing small (<1 ha) wetlands that are characteristic of the Prairie Pothole Region. A higher number and area of small, ephemeral wetlands that were on the landscape but not included in the reference data were detected based on the water permanence map. Using LiDAR data to map wetlands is particularly advantageous in the prairies because LiDAR can effectively delineate wetlands in areas with low relief and detect small depressions (Lindsay et al., 2004; Lindsay and Creed, 2005; Lang et al., 2010). Additionally, as shown by the increased perimeter-to-area ratio in our automated wetland inventory in comparison with the reference data, the object-based techniques were able to better capture the hydrologically dynamic wetland boundaries. The object-based segmentation and classification of LiDAR data contributed to the success of our method because it considers terrain homogeneity within not only the object, but also the surrounding pixels as well as the spatial location of the terrain object (Moffett and Gorelick, 2013). The automated approach to developing wetland inventories will allow managers to monitor changes in the spatial and temporal distribution of wetlands and to develop policies to reduce the vulnerability of these wetlands to further loss.

Another advantage of our wetland mapping method is that it is time independent when compared with other wetland mapping methods. When using aerial photography or other satellite imagery to map wetlands, it is often difficult to delineate the full extent of the individual wetland basin as the vegetation patterns may make establishing the boundary of the wetland difficult in certain types of wetlands (e.g. ephemeral wetlands), and wetland boundaries are extremely dynamic and dependent on the climate of a given year (Maxa and Bolstad, 2009). Further, it is dependent on the time of year and the season the remotely sensed images were collected in. To map wetlands using aerial photographs or satellite imagery, visual cues, pixel values or spectral signatures are required, which are affected by the time and date of year they are captured. One advantage of creating a wetland mapping method based on LiDAR data is that the results are less sensitive to climate and time of year to the same degree as aerial photographs and satellite images. However, to achieve the best results, LiDAR should be captured in the driest part of the year, or during dry years, to capture the full extent of any depressions because it is less able to penetrate the surface of the water.

A potential drawback of our automatic wetland mapping method is that it is sensitive to land use. Specifically, it is effective at detecting the presence of wetlands in natural and agricultural land types; however, it is less effective in urban and industrialized areas. It is unable to distinguish between natural and man-made depressions on the landscape; e.g. in urban and industrial areas, the wetland mapping method detects man-made features such as the depressions surrounding industrial tanks that are then included in the wetland inventory. Therefore, as indicated by the high commission errors in industrial areas of the watershed, the application of our method to urban areas should be carried out cautiously.

To conduct our wetland mapping method in other geographic regions, segmentation parameters and mean terrain object p_{dep} thresholds will require modification. We have provided the necessary tools within the Supporting Information (including the software used for
calculating $p_{\text{dep}}$ as well as the segmentation rule sets for eCognition Developer) for this wetland mapping method to be modified and used by wetland managers.

Wetland loss

The power-law function is based on the negative linear relationship that exists between wetland area and frequency when plotted on log–log scales. A deviation from this theoretical line indicates either wetland loss or gain. The benefits of using the power-law to estimate wetland loss are that only a wetland inventory is required for input into the power-law, and it provides a standardized method for assessing wetland loss rate estimates. However, to detect the break in slope, high-resolution wetland inventories are required as deviations from the theoretical relationship typically occur at wetland size classes that are <0.5 ha in size. A portion of the deviation from the theoretical line could be attributed to a landscape that has increased drainage or evapotranspiration that affects wetland characteristics such as soils, plants and water. This can make it difficult to differentiate wetlands from surrounding uplands. However, our wetland inventory was not created based on the spectral properties of soils, plants and water, but the presence of a depression that holds water, at least temporarily. Depressions can be detected under differing climate conditions and are sensitive to climate; thus, we assume that our deviation is due to wetland loss.

The power-law is sensitive to the selection of the area class size (i.e. the interval of wetland area on the $x$-axis of the power-law plot), the wetland area minimum and maximum thresholds to be included in the analysis and minimum frequency within the area class size bins used to generate the plot. Increasing the area class size results in an increase in both % area and % number loss because of the increase in frequency in the area classes that break from the theoretical line. Having the area class equal to the pixel size of the input data used to create the wetland inventory allows for more accurate wetland area loss estimates as a wetland within the inventory can only increase in area by the size of the pixel. To our knowledge, there are no existing studies that test the effects of modifying the power-law parameters. Previous studies have used the power-law to assess the difference in wetland distribution on the landscape over time (e.g. Van Meter and Basu, 2014), but the power-law has not been used to directly estimate the magnitude of wetland loss. In addition to the area class size, the power-law is also sensitive to the number of wetlands within a wetland inventory. The approach should not be used for small geographic areas (<500 km$^2$) with a small sample size of wetlands (<10,000 wetlands) because there may not be a high enough frequency in the area classes to form a usable power-law. For this reason, it is recommended that this analysis be carried out at a regional watershed scale at a minimum.

The accuracy of our estimated wetland loss can be compared with other estimates within the region. Environment Canada estimated wetland loss in the Canadian prairies by estimating wetland loss along a series of transects. Watmough (2011) estimated cumulative wetland loss by combining recent lost area (1985–2011) and historic (drained or filled wetland basins mapped at the time of the 1985 baseline) estimates, with a minimum mapping unit for the field campaign ranging from 0.015–0.022 ha. They used aerial photograph analyses and field verification to delineate wetlands and identify any sign of anthropogenic disturbances. This approach to monitoring wetland losses is time consuming and requires data that typically do not exist at high enough resolution over large geographic areas, and therefore cannot be used to obtain estimates of wetland loss across the entire Canadian prairies. The results of their study calculated a mean cumulative historic wetland area loss ranging from 1.6–53.2% per transection in the Beaverhill watershed region. Our area estimate of 2.6% is towards the lower end of the range of loss estimates. Watmough and Schmoll (2007) also found that the average size of lost wetlands was 0.20ha, supporting our observation of the preferential loss of small wetlands within the prairies. Several studies cite wetland loss rates for the developed areas of Canada (e.g. Bedford, 1999; Warner and Asada, 2006; Austen and Hanson, 2007). Our power-law analysis found a much lower wetland area loss within the Beaverhill watershed, a phenomenon that could be attributed to the large part of the Beaverhill watershed that is designated as parks or protected areas.

Future research needs

Future work using the power-law will focus on applying the method to the entire Prairie Pothole Region to provide a geographically based assessment of wetland loss (e.g., where is the highest historic wetland loss?) and applying the method to a time series of wetland inventories to determine the rate of wetland loss over time. This will allow us to look at wetland change in the context of wetland policies that have been implemented and allow us to examine the effectiveness of policy actions to arrest wetland loss over time.

CONCLUSION

This study demonstrates how the ability of wetland inventory mapping methods to detect small wetlands and capture edge boundary convolutedness can be improved by the use of LiDAR DEMs and object-based techniques. With the increasing availability of LiDAR data, this wetland mapping method shows promise for mapping wetlands over large geographic regions. These wetland inventories will be able to provide information on the
location of individual wetlands and the density and distribution of wetlands over landscapes, providing insight into the ability of a wetland to provide functions and ecosystem services. Further, the application a power-law function to the wetland inventory provides a simple, standardized method to estimate historic wetland loss rates. The wetland mapping and loss estimation methods developed here have the ability to improve wetland management and wetland policies.

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