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The potential role of very high-resolution imagery to characterise lake, wetland and stream systems across the Prairie Pothole Region, United States

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Abstract

Aquatic features critical to watershed hydrology range widely in size from narrow, shallow streams to large, deep lakes. In this study we evaluated wetland, lake, and river systems across the Prairie Pothole Region to explore where pan-sharpened high-resolution (PSHR) imagery, relative to Landsat imagery, could provide additional data on surface water distribution and movement, missed by Landsat. We used the monthly Global Surface Water (GSW) Landsat product as well as surface water derived from Landsat imagery using a matched filtering algorithm (MF Landsat) to help consider how including partially inundated Landsat pixels as water influenced our findings. The PSHR outputs (and MF Landsat) were able to identify ~60–90% more surface water interactions between waterbodies, relative to the GSW Landsat product. However, regardless of Landsat source, by documenting many smaller (<0.2 ha), inundated wetlands, the PSHR outputs modified our interpretation of wetland size distribution across the Prairie Pothole Region.

1. Introduction

Surface-water spatial and temporal dynamics, such as the expansion and contraction of lake systems, the filling, spilling, and merging of wetlands (Leibowitz, Mushet, and Newton 2016), or the lateral and longitudinal evolution of stream channels (Fritz et al. 2018) have critical effects on watershed hydrology (Ward 1989), biogeochemical processes (Covino 2017), and habitat functions (Schofield et al. 2018). Satellite imagery provides a key tool to characterise these interactions over spatial scales and time (Alsdorf, Rodriguez, and Lettenmaier 2007). For example, satellite imagery is commonly used to document variability in wetland or lake surface-water extent (Sheng et al. 2016; Jin et al. 2017) and flood stage along large rivers (Schumann et al. 2010; Ogilvie et al. 2015). The appropriate choice in image spatial resolution is generally agreed as the resolution at which local variance peaks (Woodcock and Strahler 1987). However, because hydrologic features that play critical roles informing watershed hydrology occur across such a wide range of object sizes (e.g. small

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wetlands and narrow streams to large lakes), it is more likely that a single appropriate image resolution for water resource applications does not exist. For instance, whereas Landsat imagery can be expected to monitor large features with ease (e.g. lakes and large wetlands), it can also be expected to miss smaller features less than its minimum mapping unit, previously shown to be approximately 9 to 11 pixels (<1 ha) (e.g. most rivers and streams, small wetlands) (Ozesmi and Bauer 2002; Knight and Lunetta 2003; Lechner et al. 2009). Consequently, a reliance on Landsat imagery may provide only a partial understanding of surface water distribution and interactions. As commercial high-resolution imagery becomes increasingly available we can explore how the spatial resolution of imagery influences our interpretation of surface water characteristics such as surface water distribution and movement.

Surface-water extent has been remotely monitored using imagery from a wide range of satellites including the moderate-resolution imaging spectroradiometer (MODIS, 1 km resolution, Schumann et al. 2010; Chen et al. 2013), Landsat (30 m resolution, Huang et al. 2011; Pekel et al. 2016), Sentinel-1 (Huang et al. 2018), commercial high resolution (2–5 m resolution, White and Lewis 2011; Whiteside and Bartolo 2015; Cooley et al. 2017), lidar (1–3 m resolution, Lang and McCarty 2009; Wu and Lane 2017), and synthetic aperture radar (SAR) (3–60 m resolution, Schmitt and Brisco 2013; Bolanos et al. 2016). Landsat surface-water products at national and global extents are becoming increasingly available. These efforts include the Global Surface Water (GSW) Landsat product produced using Google Earth Engine (Pekel et al. 2016) and USGS's Dynamic Surface Water Extent (DSWE) product (Jones 2015) both of which aim to use the entire Landsat archive to map surface water on a global and continental United States (CONUS) scale, respectively.

High accuracy statistics are commonly reported for such water products (e.g. Du et al. 2014; Mueller et al. 2016; Pekel et al. 2016). This is likely because, although most users understand the detectable limits of Landsat (e.g. Ozesmi and Bauer 2002; Knight and Lunetta 2003; Lechner et al. 2009), accuracy statistics generated using random sampling can be expected to reflect the size distribution of the waterbodies, which can potentially obscure the spatial distribution of error. For example, if a large lake comprises 90% of the surface water across the watershed, we can expect that approximately 90% of the validation points will occur within the lake. However, if the lake flows into a major river via a narrow conveyance, this single narrow channel may have a disproportionate impact on the hydrology of the watershed (e.g. Shaw, Pietroniro, and Martz 2013; Spence and Phillips 2014), but the ability of a remote sensing product to monitor such a narrow conveyance is unlikely to be reflected in commonly reported accuracy statistics. Although the effect of object size on accuracy in remote sensing is intuitive, efforts to quantify this phenomenon across different remote sensing applications are very limited in the literature (e.g. Castilla et al. 2014), and its effect on our interpretation of surface water patterns has not been characterised to date.

In this study we compared how our interpretation of surface water distribution and surface water movement between waterbodies were informed by using pan-sharpened high-resolution imagery (0.5 m resolution) relative to Landsat imagery (30 m resolution) across landscapes dominated by (1) wetlands, (2) lakes, and (3) rivers (seven sites total). We

selected the Prairie Pothole Region as our area of interest as (1) the region exhibits substantial interannual variability in surface water extent necessitating the need for routine surface water monitoring (Huang et al. 2011; Beerli and Phillips 2007), (2) other barriers to remotely evaluating surface-water (e.g. trees, topographical shade) are limited, enabling us to isolate the interaction between imagery and aquatic system configurations, and (3) the median size of wetlands in the region is only 0.16 ha (Wu and Lane 2017), less than two Landsat pixels, meaning moderate resolution satellites may be inadequate. Whereas the PSHR images (0.5 m resolution) can still be expected to underestimate surface water, especially narrow features (e.g. swales, ephemeral channels), it currently represents the ‘cutting edge’ of our ability to remotely detect water at a landscape scale (Amro et al. 2011) (Figure 1). We explored the research question, where can high-resolution imagery, relative to Landsat imagery, enhance our understanding of surface water distribution and movement across the Prairie Pothole Region?

2. Methods

2.1. Study area

The Prairie Pothole Region (PPR) extends from Saskatchewan and Alberta, Canada, south into the upper Midwestern United States. Within the United States, the PPR extends across parts of North Dakota, South Dakota, Montana, Minnesota, Iowa and Nebraska (Figure 2). The PPR is part of the temperate prairie and west-central semi-arid prairie ecoregions (Level II, Omernik and Griffith 2014). The region is characterised by landscape features formed during its recent glacial history, including drift plains, large glacial lake basins and shallow river valleys. These portions of the PPR support row crop agriculture (59%). Areas where glaciers left deposits of uneven glacial till are dominated by grasslands (18%) and livestock grazing (10%) (Homer et al. 2015). Mean annual precipitation (1981–2010) across the selected sites noted below ranged from 490 to 635 mm yr⁻¹ (PRISM Climate Group 2012). Mean temperature maximum and minimum (1981–2010) across the selected sites range from 9.6 to 15.8°C and -1.9 to 2.6°C, respectively (PRISM Climate Group 2012).

2.2. Image and site selection

Sites (n = 7) were selected across the PPR to represent different lentic and lotic systems including (1) wetlands, (2) lakes, and (3) rivers (Figure 2). Site selection was guided in part by the representativeness of a site and in part by the availability of high resolution imagery acquired from DigitalGlobe (Westminster, CO). A total of 19 high-resolution images (Worldview-2, QuickBird-2, GeoEye-1) and 13 Landsat images (TM, ETM+, OLI) were processed (Table 1). Images were restricted to snow-free conditions (May–October). When possible, we processed two high-resolution images per site representing different dates to account for the potential influence of climatic and antecedent conditions. A corresponding Landsat image selected by nearest date and cloud-free (<10% cloud for the portion overlapping the high-resolution image extent) was compared with the high-resolution images. The date gap between the high-resolution and Landsat images averaged 16 days (ranged 4 to 40 days) with no average bias in the relative timing of the high-resolution images versus the Landsat images (<1 day).

Sites with a high density of wetlands were represented by the USGS Cottonwood Lake study area (and nearby wetlands) (47°7'43" N, 99°8'46" W), near Jamestown, North Dakota and wetlands adjacent to the Waubay National Wildlife Refuge (Waubay NWR wetlands) (45°27'35" N, 97°31'59" W) (Figure 2). When wetlands were defined using the National Wetlands Inventory (NWI) dataset (USFSW 2010), the Cottonwood Lake site showed a high density of very small (<0.2 ha) wetlands (7.8 to 9.2 wetlands per km² for the 2011 and 2015 image extents, respectively), as well as a high density of small (0.2 to 1.0 ha) wetlands (3.7 and 4.7 wetlands per km² for the 2011 and 2015 image extents respectively). The Waubay National Wildlife Refuge wetland site showed a density of 4.5 to 4.8 wetlands per km² of very small (<0.2 ha) wetlands, for the 2004 and 2012 image extents, respectively, and a density of 2.3 and 2.5 wetlands per km² of small (0.2 to 1.0 ha) wetlands for the 2004 and 2012 image extents, respectively. The Cottonwood Lake study area was also included because of the availability of field-collected water level data that was used to validate both the Landsat and high-resolution imagery outputs (see section 2.6). For lakes, we were interested in how the sources of imagery differentially mapped lake expansion, so lakes that exhibited an expansion of extent as conditions became wetter were intentionally selected (Vanderhoof, Alexander, and Todd 2016). The Waubay NWR lakes were selected as the area contains multiple large lakes including Waubay Lake, Spring Lake, Rush Lake, Blue Dog Lake, and Bitter Lake (Table 2). Additional lake sites included Barnes Lake in North Dakota, west of Arrowwood National Wildlife Refuge, Horseshoe Lake, and a third lake (unnamed) just southwest of Horseshoe Lake (Table 2) (to be referred to as the Horseshoe Lakes). The latter two lakes are located just north of the Sheyenne River in North Dakota. River sites include a section of the Niobrara River in northern Nebraska (25 km reach, 42°52'13" N, 98°55'29" W) and the Sheyenne River in North Dakota (39 km reach, 47°50'43" N, 98°56'4" W), as well as the tributaries present within the image extent were used to represent our river sites (see Figure 2). All visibly wet (as observed using the raw pan-sharpened high-resolution images) rivers and streams, as defined by the High Resolution National Hydrography Dataset (NHD) (USGS 2013), within the image extents were included in the river analysis. Across the study areas, static data layers (e.g. the NWI and NHD) identified a total of 8911 wetlands, totaling 8843 ha, 8 lakes totaling 4294 ha, and 23 streams and rivers with a total length of 142 km.

2.3. High-resolution image processing

The high-resolution images were classified as water and non-water. Climate conditions at the time of the image collection were characterised using a monthly Palmer Hydrological Drought Index (PHDI) and the Standardized Precipitation index over 24 months (SP24) (NOAA NCDC 2014). Wetter images were selected for inclusion as available so that surface-water expansion would be potentially present on the landscape. A list of the high-resolution images (Worldview-2, QuickBird-2, GeoEye-1) used in the analysis is shown in Table 1. The images were converted to surface reflectance using Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) in ENVI (Boulder, CO) (Adler-Golden et al. 1998, 1999). The high-resolution images (Worldview-2, QuickBird-2, GeoEye-1) were delivered at 2 m resolution. We used the Gram-Schmidt pan-sharpening algorithm (Laben and Brower 2000) to pan-sharpen each spectral band to 0.5 m resolution. Surface water was identified using the Maximum Likelihood (ML) supervised classification, a popular

statistical classifier (e.g. Lin et al. 2015). We tested multiple classification approaches including the Matched Filtering algorithm but found that ML out-performed other techniques. If water was spectrally diverse across the image (i.e. clear, dark water, shallow, turbid water, water with high chlorophyll content), then multiple categories of water were classified per image (for example (1) dark water, (2) algae-covered water, and (3) turbid water) in addition to classifying other non-water classes including (4) photo-synthetic vegetation, (5) non-photosynthetic vegetation, and (6) bare soil. This approach reduced the spectral heterogeneity within each of the water classes whilst enabling the spectral signature of water to be image specific. A Frost Filter with a window size of 3 pixels by 3 pixels was applied to the classified image to reduce speckling both within and between waterbodies. The classes were then reclassified to a binary classification (water, not water). Roads were a common source of surface water extent disruption captured by the high-resolution imagery. To account for this, following image binary classification, if the water body was continuous on both sides of the road we assumed a culvert was present and manually edited the surface-water extent to extend across the road. This manual step was taken to improve the accuracy of our efforts to quantify surface water movement between water bodies. This output will be referred to as the PSHR imagery.

2.4. Landsat image processing

The purpose of this analysis was not to generate novel image processing approaches, but instead to characterise the relative impact of products on our interpretation of surface water distribution and interactions. To this end, we used a Landsat image processing approach previously applied across the PPR (Vanderhoof, Alexander, and Todd 2016; Vanderhoof et al. 2018). The images were delivered from the U.S. Geological Survey having been converted to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (Masek et al. 2006). Landsat ETM+ images with the scan-line corrector off were gap-filled using a Gapfill plug-in tool (triangulation method) in ENVI (version 5.3, Harris, Melbourne, Florida). A minimum noise fraction transformation tool was used to reduce random noise across the image (Green et al. 1988). The per pixel fraction water was identified using the Matched Filtering algorithm in ENVI (Turin 1960; Vanderhoof, Alexander, and Todd 2016). This algorithm is ideal for cases in which the end user is only interested in one or a few target endmembers (e.g. water). The algorithm quantifies the presence of the target endmember whilst ignoring the unknown composite background (Frohn et al. 2012). This algorithm is locally trained on water spectral signatures derived from open-water polygons manually selected within each path/row, resulting in a water signature specific to each image. Three to four polygons (minimum size of 1 ha per polygon) per path/row were selected, with approximately 20 ha total training area per path/row combination. The output values were linearly stretched to maximize the spread of pixel values, enhancing our ability to distinguish water from non-water pixels. A per-pixel threshold value of 0.3 was selected to discern and bin water (≥ 0.3) and non-water (< 0.3) pixels, and has been previously shown to allow wetlands larger than 0.2 ha to be reliably (defined as $> 70\%$ of the features of that size class) detected in the Prairie Pothole Region (Vanderhoof et al. 2018). The National Land Cover Database (NLCD)(2011) was used to mask out impervious surfaces, defined as low, medium and high-density development

(Homer et al. 2015), which can show spectral confusion with surface water. This output will be referred to as the MF (matched filtering) Landsat.

2.5. Global surface water Landsat product

In addition to the MF Landsat, the monthly GSW Landsat product (Pekel et al. 2016) was also included to provide a sense of the amount of variability that can occur between Landsat products. This product was generated using a machine learning approach and applied to the entire Landsat archive (1984–2015) and has reported errors of omission of <5% and errors of commission <1% when validated at a global scale (Pekel et al. 2016). As described by Pekel et al. (2016), water was classified by first generating class cluster hulls that described the distribution of water spectral signatures from Landsat. The visual analytic clusters were then used to guide a procedural sequential decision tree using Landsat spectral bands and ancillary data layers. For pixels that were not unambiguously assigned, evidential reasoning was used to guide class assignment using consideration of geographic location and temporal trajectory (Pekel et al. 2016). Additional details in the image processing for the GSW Landsat product are provided in Pekel et al. (2016). We downloaded the monthly rasters from Google Earth Engine (image collection: JRC Monthly Water History v1.0 (1984–2015)). Monthly rasters were selected to ensure that the same Landsat images processed by us (MF Landsat) were also processed by the GSW Landsat product (Table 1). Because the rasters are delivered from Google Earth Engine as binary water/not water, we were unable to gap-fill months comprised only of Landsat-7 ETM+ SLC-off images ($n = 2$). Where possible, we visually interpolated these data gaps (e.g. correcting where large lake features were continuous on either side of data gaps). Because the Landsat 7 ETM+ (scan-line corrector off) represents a substantial portion of the Landsat archive we felt it was important to consider its influence on our ability to characterise surface water.

2.6. Surface-water extent validation

The binary (water and non-water) images were validated using field-collected water level data. Water levels (one per wetland) are regularly measured at a series of temporary and permanent wetlands located at the Cottonwood Lake study area near Jamestown, North Dakota (Mushet, Rosenberry, and Solensky 2016). The water levels were converted to surface-water extent using a lidar digital elevation model (DEM) (1 m resolution) that included bathymetry of waterbodies for which lidar did not detect the feature bottom (Mushet, Roth, and Scherff 2017). Water levels were identified for the date closest to the date of image collection (Table 3). At each water level measurement point, the water depth (e.g. 2 m) was added to the bathymetry DEM to create a water elevation raster. The elevation at the point of measurement was then used to reclassify the raster where elevations lower than the water depth were classified as water. Because the elevation of the water surface is likely to be inconsistent across space, the surface-water extent was generated individually for each wetland (and water-level measuring point). Water validation points were randomly selected across the generated surface-water extent, and non-water validation points were randomly selected from within a buffer (between 3 m and 30 m from the water edge for the PSHR imagery, between 30 m and 100 m from the water edge for Landsat (MF and GSW)) around the wetland features (Figure 3). Validation points (100 water, 100 non-water) were independently generated for each imagery resolution and for each of two dates (29 August

2011 and 24 July 2015), providing a total of 200 water points and 200 non-water points for validation of each classified image (PSHR images, MF Landsat, GSW Landsat product). Validation points were separated by a minimum of 2 m for the PSHR imagery and 30 m for the Landsat products. Metrics presented included overall accuracy, omission error, commission error, dice coefficient, and relative bias. Omission and commission errors were calculated for the category 'water'. The dice coefficient is the conditional probability that if the reference dataset identifies a pixel as water, the output product will as well, integrating errors of omission and commission (Fleiss 1981). The relative bias is the proportion that surface-water extent is under (negative) or overestimated (positive) relative to the total surface-water extent in the reference data (Bainbridge 1985).

Using the PSHR surface-water extent as our reference dataset, additional accuracy statistics were also generated for the Landsat products (MF Landsat and GSW Landsat) by randomly generating points, (1) across all sites (6000 water points, 6000 non-water points), as well as (2) independently generated points for each aquatic system, with 200 water points and 200 non-water points from each image extent and aquatic system ($n = 1600$ for wetlands, $n = 2000$ for lakes, $n = 1600$ for rivers). To generate the validation points across all sites, the PSHR surface-water extent was used for one date per site (Cottonwood – 2011, Wildlife Refuge wetlands – 2004, Wildlife Refuge lakes – 2015, Barnes Lake – 2011, Horseshoe Lake – 2015, Sheyenne River – 2015, Niobrara River – 2006, Table 1).

2.7. Surface-water extent comparison

Surface-water extent mapped by the PSHR imagery was compared to surface-water extent mapped by the MF Landsat and the GSW Landsat product in each aquatic system. The NWI wetland dataset, which is meant to represent wetland extent under median climate conditions (U.S. Fish and Wildlife Service (USFWS) 2010), was used to define individual wetlands in reference to the mapped surface-water extent. The wetland dataset has only been partially updated so that according to the metadata, the wetland extent was generated between 1977–2016. Wetland boundaries, internal to a single, continuous NWI wetland, were dissolved. The co-occurrence of more than one dissolved NWI wetland or lacustrine feature within a single, continuous surface-water polygon was used to quantify the total number of surface water interactions and the creation of wetland clusters. For example, the merging of three wetlands into a single continuous surface-water area creates one wetland cluster and three wetland-to-wetland surface water interactions. Each Landsat path/row output was clipped to the extent of its corresponding high-resolution image to ensure that the same area was being compared. This meant that for each site, an image date represented a unique extent across that site. Consideration of surface-water features was restricted to the type of aquatic system being represented in that image. For example, we excluded lake and river features when assessing wetland hydrologic characteristics. Similarly, in images representing lakes, only surface water continuous with NWI lacustrine features were considered, whereas in images representing river systems, only streams and river channels were considered.

For wetland systems, we compared the (1) total surface-water extent, (2) number of inundated NWI wetlands, (3) total count of NWI wetland-to-NWI wetland surface-water interactions, and (4) the number of clusters created by NWI wetlands merging. For lakes we

compared the number of NWI features (wetlands and lakes) detected within continuous lake perimeters as well as the total continuous lake surface-water extent. In river systems we compared the percent of the river mapped by river width and data source. The High Resolution NHD (1:24,000) was used to define streams (USGS 2013). All high-resolution NHD lines overlapping a high-resolution image extent were considered. The pan-sharpened natural color image was used to eliminate high-resolution NHD lines that were visually identified to be dry at the time of image collection. We note that a river could be observed visually to contain water, and thus included in the analysis, but inadequately mapped as wet by the PSHR imagery because of spectral confusion during image processing and classification. For rivers with standing or flowing water, river width was calculated as the average of 20 randomly selected wetted-width measurements taken along the length of each river using the pan-sharpened natural-color image. For each 'wet river' (a subset of the NHD high resolution stream lines), 100 points were randomly generated along the center line. This totaled 23 streams ($n = 2300$ points) across the sites, dates and different streams/ivers within each site and date. The percent of the river points classified as wet by each imagery was recorded.

3. Results

3.1. Accuracy of surface water outputs

The Cottonwood Lake study area water level field data indicated that water was present in eight of the wetlands measured. For the two dates used to validate the images, the validation wetlands ranged from 0.2 to 17.6 ha in size and averaged 3.8 to 4.2 ha in size (Table 3). The PSHR imagery showed an overall accuracy of 94% and a dice coefficient of 93% with a 12% omission and 0.6% commission error in mapping surface-water extent (Table 3). This can be compared to the 22 and 42% error of omission observed when validating the MF Landsat and GSW Landsat products, respectively, with the water level field data (Table 4, overall accuracy 87 and 79%, respectively). Relative bias was negative for all three data sources indicating that surface-water extent tended to be underestimated (Tables 3 and 4).

3.2. Total surface-water extent

We found that in mapping total surface-water extent across the PPR study sites, the PSHR imagery documented approximately 10 to 15% more surface water than Landsat outputs. When points were randomly selected across all PPR study area extents (wetlands, lakes, and river scene extents, $n = 12,000$), using the PSHR inundation extent to define the reference condition, the MF and GSW Landsat showed a 7 and 16% error of omission, a 2 and 1% error of commission, and a relative bias of -5% and -15%, respectively, for surface water. Accuracy statistics by aquatic system can help us understand the distribution of the surface water missed by Landsat, relative to using PSHR imagery. Errors of commission for surface water were <5% across all systems and Landsat products, whereas errors of omission for surface water ranged widely and were highest in river systems. The MF Landsat had errors of omission of 4%, 8%, and 64% for lake, wetland, and river systems, respectively. Similarly, errors of omission for the GSW Landsat were 6%, 14%, and 84% for lake, wetland, and river systems, respectively. In wetland systems, we found that the two Landsat products showed similar errors of omission (8% vs 14%), whereas the PSHR imagery

mapped 1% less and 26% more wetland surface water than the MF Landsat and GSW Landsat products, respectively.

3.3. Characterizing the distribution of surface water

Having an accurate understanding of the spatial distribution of surface water, in addition to the total quantity of surface-water, is often of interest for applications such as the management of nutrient loading and wildlife habitat. Not surprisingly, the PSHR imagery provided a substantial advantage in detecting small, inundated wetlands, as well as river and streams. The Prairie Pothole Region (PPR) contains a higher density of small (<1 ha) and in particular very small (<0.2 ha) NWI wetlands relative to regions west, south and east of the PPR (Figure 4). According to the NWI dataset, the density of very small wetlands (7.7 and 5.0 wetlands per km²) and small (2.9 and 2.8 wetlands per km²) wetlands is greatest across parts of North and South Dakota, respectively (Figure 4). The large number of small wetlands that are mapped by the NWI dataset often raises concern regarding the appropriateness of using Landsat imagery in a region dominated by such small wetlands. The wetland image dates used in the analysis ranged from April through September, therefore more accurately representing the growing season and not the spring peak in wetness. Only 42% of the NWI wetlands across our wetland sites were mapped as inundated by the PSHR imagery. The remaining 58% of the NWI wetlands is likely a mix of ephemeral wetlands dry at the time of image collection, as well as wetlands that have been lost, or are no longer functioning as wetlands attributable to agriculture and associated tile drainage (Werner et al. 2016). If the number of wetlands detected by Landsat is compared instead to the wetlands mapped as inundated by the PSHR imagery, we can more adequately evaluate the advantage provided by the PSHR imagery outputs relative to Landsat to map the distribution of inundated wetlands. The MF Landsat mapped 28% of the NWI wetlands as inundated but found 65% of the wetlands identified as inundated by the PSHR imagery. The GSW Landsat, meanwhile, mapped 20% of the NWI wetlands as inundated, but found 46% of the wetlands identified as inundated by the PSHR imagery. An example of this is shown in Figure 5, where we see considerable variation in the ability to map the surface-water extent of smaller wetlands in the northern portion of the study area. We found that the differential ability to detect small wetlands can change our interpretation of the size distribution of wetlands (Figure 6(a)) but appears to have very little impact on our interpretation of the contribution of different water body sizes to the total surface water extent (Figure 6(b)). This suggests that using PSHR imagery we would interpret the landscape as dominated by small (<0.2 ha) wetlands, whereas using Landsat imagery we would interpret the landscape as dominated by moderate-sized wetlands (0.2–8.0 ha). In contrast, all sources agreed that most of the total surface water occurred in large (>8.0 ha) waterbodies.

Outside of very large rivers and large floods, monitoring rivers and streams is typically not possible due to the narrowness of the features. Across the region, for example, rivers potentially identifiable with Landsat (>30 m wide), as identified by the North American River Width Data Set (NARWidth) (Allen and Pavelsky 2015), represent, on average, 1% of total stream length, as mapped by the High Resolution NHD dataset. Across the two river sites, we mapped a total of 23 streams and rivers, where 14 showed a width of <10 m, 4

showed a width averaging 10 m to 30 m, and 5 showed a width of >30 m (Table 5). Although most streams and rivers are simply too narrow to be detected with Landsat imagery, the MF Landsat mapped approximately double the stream and river length relative to the GSW Landsat product (22 and 10% for rivers 10 to 30 m wide, and 71 and 37% for rivers 31 to 85 m wide, for MF Landsat and GSW Landsat product, respectively) (Table 5 and Figure 7). In contrast, the PSHR imagery mapped 37%, 72%, and 93% of rivers <10 m wide, 10 to 30 m wide and 31 to 85 m wide, respectively (Table 5).

3.4. Characterizing surface water movement

As landscapes become wetter, they begin to hydrodynamically interact via surface flow through both channelised conveyances as well as fill-spill and fill-merge processes. Because water carries nutrients, pollutants, and biota, accurately characterizing its movements is critical to predicting water quality (Fritz et al. 2018; Lane et al. 2018). In wetland systems, the PSHR imagery found only 7% more wetland to wetland interactions relative to the MF Landsat, but 91% more wetland to wetland interactions than the GS Landsat (Table 6). Similarly, the PSHR imagery found an identical number of wetland clusters as the MF Landsat, created as wetlands merge together, but 62% more wetland clusters than found with the GSW Landsat (Table 6). Lakes are also abundant across parts of the PPR (Figure 8). Unexpectedly, the findings were very similar in lake systems. The PSHR imagery detected only 2% more NWI wetlands within the continuous lake extent than the MF Landsat, but 57% more NWI wetlands than the GSW Landsat. The relatively minor difference in the abundance of wetland-to-wetland interactions between the PSHR imagery and the MF Landsat can be largely attributed to Landsat missing some narrow interactions between wetlands, but also falsely detecting some interactions or overestimating interactions in other areas (Figure 9). Conversely, the PSHR imagery detected narrow interactions but also detected narrow disconnections, or situations where the surface-water extent contracted sufficiently that individual wetlands emerged (Figure 9). Although water in these cases, is still likely moving in the shallow-subsurface, the rate of movement can be expected to be impacted. The more conservative surface-water extent defined by the GSW Landsat meant that the product tended to miss narrower interactions and consequently showed a 15% smaller, continuous lake surface-water extent (Table 7) and fewer wetland interactions in both wetland and lake systems. Figure 10 shows an example of where MF Landsat also missed narrow interactions, for example in Figure 10 the PSHR image detected a narrow interaction between the lake and wetlands north of the lake that was missed by the MF Landsat. Also shown in Figure 10, the GSW Landsat product, missed a key surface-water interaction between Barnes Lake and the lake just north of it, producing a much smaller total lake extent. These results indicate that relatively narrow (<40 m wide) interactions or conveyances can be important in lake systems too, not just wetland systems. We found that as lake levels rise, wetlands are not always subsumed – instead topography can maintain relatively narrow (<40-m wide) interactions between lakes and nearby lakes or wetlands.

4. Discussion

Enhancing our understanding of water distribution and movement across regions such as the Prairie Pothole Region is of high importance. As the ‘duck factory’ of North America,

smaller wetlands across the PPR are highly valued as waterfowl habitat (Ballard et al. 2014), however anthropogenic-related wetland losses across the region have occurred disproportionately for smaller wetlands, losses attributable to agricultural development, including tile drainage, and climate-induced drying (Johnston 2013; Dahl 2014). In river systems, improving our ability to monitor river stage has multiple applications including enhancing flood predictions, as well as informing the distribution of flow to downstream gaged points, and improving river management (Schumann et al. 2010; Demarchi, Bizzi, and Piegay 2016). In addition, under wetter conditions, surface-water extent expands, and movement of water can occur between wetlands via ‘fill-and-spill’ (Tromp-van Meerveld and McDonnell 2006) or ‘fill-and-merge’ (Vanderhoof and Alexander 2016; Leibowitz, Mushet, and Newton 2016). The movement of this water is highly relevant as it informs the movement of nutrients, sediment and pollutants across a watershed, profoundly effecting water quality (Leibowitz, Mushet, and Newton 2016) and wildlife habitat suitability (Krapu et al. 2004; McLean, Mushet, and Stockwell 2016).

In this study we found that PSHR imagery, relative to Landsat imagery, provided a substantial advantage in documenting small wetlands and rivers. Although this finding was not unexpected, what was more surprising was that the difference was substantial enough to change our interpretation of the wetland size distribution across the land-scape (Figure 6A), a finding relevant, for example, to predicting the movement of (or habitat availability for) aquatic species, such as insects, amphibians and reptiles that use multiple waterbodies (Schofield et al. 2018). Another surprising finding was that Landsat, relative to the PSHR imagery, can potentially provide similar estimates of wetland-to-wetland and wetland-to-lake water movement as well as the creation of wetland clusters, although with less positional accuracy. In addition, we found that relatively narrow (<60 m wide) conveyances were not restricted to wetland systems, but often still relevant in lake systems. However, the substantial underestimation of these metrics by the GSW product suggests that considering mixed water pixels is critical to not only mapping smaller wetlands (<1 ha), but also for detecting key surface-water interactions. The automation of estimating the sub-pixel water fraction from Landsat imagery over large areas and long-time periods could therefore be used to improve upon national to global Landsat products (e.g. DeVries et al. 2017).

The performance of a remote sensing product can be highly variable even after controlling for the source of imagery (e.g. Feyisa et al. 2014; Fisher, Flood, and Danaher 2016). Variable performance in water resource applications can occur, in part, because of the heterogeneity in the spectral characteristics of waterbodies, which can vary with chlorophyll concentration, turbidity, water depth, waterbody bottom material, and observation conditions (Ozesmi and Bauer 2002; Arst 2003; Zomer, Trabucco, and Ustin 2009). As most traditional classifiers depend on homogeneity across the region of interest (Foody, McCulloch, and Yates 1995; Brown, Gunn, and Lewis 1999), as feature heterogeneity increases, for example when both open water and vegetated water occur, misclassification errors can also increase (Ozesmi and Bauer 2002). Approaches that accommodate high heterogeneity, for example by classifying mixed (e.g. partially vegetated) pixels as water, may be able to better document surface water characteristics relative to an approach that primarily maps open water, such as the GSW Landsat product. It is also possible that machine learning approaches, which are increasing in popularity (e.g. Tuia et al. 2011; Hird et al. 2017), may

out-perform more traditional classifiers such as ML or the Matched Filtering algorithm, particularly when applied at a regional scale.

Whereas the finer spatial resolution of commercial high-resolution imagery can enhance our ability to characterize surface water distribution and movement (e.g. Cooley et al. 2017), surface water patterns across regions such as the PPR, can be expected to vary not only interannually, but also seasonally (Beeri and Phillips 2007), peaking with snowmelt and precipitation events (Leibowitz, Mushet, and Newton 2016). DigitalGlobe's satellites, however, do not collect data at regular intervals, and although other sources of high-resolution data, such as Planet's constellations of CubeSats, are available at regular intervals, the cost of imagery (e.g. DigitalGlobe, Planet) may limit its role in operational monitoring of surface water distribution and movement. Considering these challenges, it might instead be preferable to utilize freely available sources of imagery such as Sentinel-1 and Sentinel-2 (10 to 20 m resolution) that improve upon Landsat spatial resolution whilst retaining regular collection intervals (e.g. Huang et al. 2018). Even given limited high-resolution imagery, however, useful data can still be extracted that could be potentially integrated into a dataset such as the NWI dataset. Patterns of surface water as mapped by high-resolution imagery could be used, for example, to help characterize minimum and maximum surface water extents, and corresponding changes in wetland size and frequency (influenced by wetlands wetting up as well as merging or emerging). This data would be useful to (1) identify wetlands that are no longer present or functional due to agricultural activities such as tile drainage (Werner et al. 2016), as well as (2) help predict how land use changes or shifts in climate patterns will impact the movement of nutrients and pollutants (Lane et al. 2018).

To explore how single collection PSHR images could be used to identify potential water movement, for example, we visually identified (using the PSHR raw images) dry conveyances (e.g. swales, ephemeral channels) between wetlands and between lakes and wetlands that showed evidence of regular water presence but was either dry or non-continuous at the time of the image collection (Figure 11). In lake systems, where extent has been shown to reflect longer term trends in wetness relative to wetlands (e.g. Zhang, Schwartz, and Liu 2009), visible, potential conveyances were found to represent a relatively minor percent of wetland-to-lake interactions (6% of all identified wetland-to-lake interactions). However, across wetland sites the potential conveyances represented a potential 46% increase in the total number of wetland-to-wetland interactions, even when using images collected during wet years. These initial findings support the need to characterise potential episodic or short-duration interactions (e.g. Evenson et al. 2016; Hay et al. 2018), or move towards near-daily surface-water products that include multiple sensors such as both Landsat and Sentinel-2 (DeVries et al. 2017) or incorporate fine to moderate resolution SAR imagery (e.g. Radarsat-2, Sentinel-1) to map conditions through cloud cover (Miles et al. 2017; Pham-Duc, Prigent, and Aires 2017).

We must also consider how applicable our findings are to other landscapes. The river, lake and wetland sites examined in this study were spread across multiple states (North Dakota, South Dakota, and Nebraska) but restricted to the Prairie Pothole Region. Sites were selected across this region to have a relatively high density of wetlands, large lakes, and surface-water interactions (Beeri and Phillips 2007; Huang et al. 2011; Vanderhoof, Alexander, and

Todd 2016). The findings presented here can be expected to be relevant to waterbodies across other non-forested regions (e.g. systems dominated by grassland, shrub/scrub or savannah) and to be particularly relevant to floodplains, permafrost landscapes and other formerly glaciated landscapes that often exhibit low topographic gradients and low rates of infiltration that can lead to highly dynamic surface water storage (Hamilton, Sippel, and Melack 2004; Yao et al. 2007; Aragón, Jobbágy, and Viglizzo 2011; Kuppel et al. 2015). We might also expect the findings to be relevant in wetlands dominated by water-adapted vegetation, where products restricted to open water will likely underestimate spectrally mixed pixels. Examples of such areas include the Everglades in Florida (Jones 2015), as well as wetlands dominated by plant species such as cattails (*Typha* spp.) or sedges (*Scirpus* spp.) (e.g. palustrine emergent wetlands). However, the findings may be less applicable in heavily forested regions (including areas with forested wetlands) where both PSHR imagery as well as Landsat imagery may underestimate surface-water extent during the growing season when tree cover can mask water. In such regions, mapping surface water with multispectral imagery is typically restricted to leaf-off periods (e.g. Vanderhoof et al. 2017) or may require a reliance on SAR imagery (e.g. Hess et al. 2015; Schlaffer et al. 2016).

This study found that input-data granularity influences our interpretation of surface water distribution and movement that can potentially impact subsequent applications of surface water monitoring such as resource management or modeling efforts. For example, hydrologic and biogeochemical model outputs may change markedly depending on the defined expanse of wetted areas, flowpath extent, active contributing areas, and processing length (e.g. Baker, Weller, and Jordan 2007; Nadeau and Rains 2007; Rains et al. 2015; Golden et al. 2017). Whereas Landsat can provide adequate estimates of total surface water extent, for applications in which knowledge of surface water distribution and movement through a watershed, between waterbodies, or into the stream network is important (e.g. Golden et al. 2016; Evenson et al. 2018), either PSHR imagery, a Landsat product that considers partially inundated pixels, or an alternative finer resolution source of imagery (e.g. Sentinel-2 at 10 to 20 m resolution) may be necessary.

5. Conclusion

This study was unique in contrasting high-resolution imagery with Landsat products not just across diverse aquatic systems, but also comparing their ability to characterise surface-water movement between waterbodies, which can have important consequences for watershed hydrology (Shaw, Pietroniro, and Martz 2013; Golden et al. 2016). Mixed pixel approaches to process Landsat, relative to PSHR imagery, documented similar estimates of total surface water extent and frequency of interactions between waterbodies, however, by documenting many more small, inundated wetlands, the PSHR imagery in the PPR, modified our interpretation of the landscape-scale wetland size distribution. Our findings also suggest that whilst global water products such as the GSW Landsat product can allow for an unprecedented improvement in our understanding of large-scale patterns in surface-water distribution, it may be less appropriate for regional or localised applications, particularly in regions dominated by a high density of small wetlands, or where the distribution of water in smaller waterbodies or the movement of surface-water as aquatic systems interact via conveyances (e.g. swales, rivers, and streams) is of interest. With the launch of an increasing

number of satellites that collect SAR imagery (e.g. Sentinel-1) or higher-resolution imagery, including Sentinel-2 (10 to 20 m resolution) as well as networks of microsatellites (e.g. Dove, RapidEye (5 m resolution, Planet, San Francisco)), opportunities to monitor surface-water extent and interactions between aquatic systems at finer spatial resolutions and near-daily return intervals are rapidly becoming a possibility. The increased availability of such high-resolution imagery necessitates an improved understanding of where multi-spectral high-resolution imagery can enhance our understanding of surface water storage, distribution and movement.

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Figure 1.

Comparisons of a river using (a) Landsat TM imagery (30 m) versus (b) Worldview-2 imagery (2 m), and a zoomed-in portion of the river using (c) Worldview-2 versus (d) pan-sharpened Worldview-2 imagery (0.5 m). The river is a tributary to the Niobrara River in northern Nebraska. Comparisons of a wetland using (e) Landsat TM imagery versus (f) Worldview-2 imagery, and a zoomed-in portion of the wetland using (g) Worldview-2 versus (h) pan-sharpened Worldview-2. The wetland is adjacent to the Waubay National Wildlife Refuge in South Dakota. Each comparison is shown at identical scales. Copyright 2006 and 2012 Digital Globe, Next View License.

Figure 2. Distribution of sites representing wetlands, lakes, and rivers across which surface-water interactions and mapped surface-water extent were characterised using locally trained Landsat and globally trained Landsat, with high-resolution imagery used as the reference dataset. Copyright 2006 and 2012 Digital Globe, Next View License.

Figure 3.

An example (27 July 2015) of the surface-water extent derived from the Cottonwood Lake study area water level measurements and the corresponding randomly selected validation points used to validate the high-resolution surface-water extent. P wetland codes refer to historically permanent wetlands and T wetland codes refer to historically temporary wetlands.

Figure 4. Heat maps showing the point density of National Wetlands Inventory wetlands (a) smaller than 0.2 ha in size and (b) between 0.2 and 1.0 ha in size.

Figure 5.

A comparison of a section of the Cottonwood Lake Study Area as (a) seen by high-resolution imagery, (b) mapped from pan-sharpened high-resolution (PSHR) imagery, (c) seen by Landsat, (d) mapped by locally trained (MF) Landsat, (e) mapped by the Global Surface Water (GSW) monthly Landsat product maximum. Copyright 2011 Digital Globe, Next View License.

Figure 6.

The distribution of wetlands across the Cottonwood Lake Study Area and the Waubay National Wildlife Refuge area defined as (a) the frequency of wetlands in each size class as a percent of all wetlands identified, and (b) the summed area of wetlands in each size class as a percent of all wetlands identified. Using PSHR imagery we would interpret the landscape as dominated by small (<0.2 ha) wetlands, whereas using Landsat imagery we would interpret the landscape as dominated by moderate-sized wetlands (0.2–8.0 ha) (a), however all sources agree that most of the water occurs in large (>8.0 ha) waterbodies (b) Error bars indicate standard error estimates. NWI: National Wetlands Inventory wetlands, PSHR: pan-sharpened high-resolution, MF: locally trained, GSW: Global Surface Water monthly product.

Figure 7.

Mapped river extent across the braided Niobrara River, Nebraska (4 to 150 m wide) and a tributary (8 m wide) (top) and the Sheyenne River, North Dakota and a small tributary (2 to 3 m wide) (bottom). A comparison of stream extent using a Worldview-2 image (a, b) and QuickBird-2 image (e, f), matched filtering (MF) Landsat 8 (top, c) and MF Landsat 5 (bottom, g), and the Global Surface Water monthly product (d and h). The raw high-resolution images are used as the back-ground in all panels. Copyright 2003, 2015 Digital Globe, Next View License.

Figure 8.

Point density of lakes where each point represents a National Wetlands Inventory polygon classified as lacustrine and >20 acres in size. Points were converted to density using a kernel function where each pixel was 100 km² and the search radius was defined using a spatial variant of Silverman's Rule of Thumb.

Figure 9.

A comparison of surface-water extent as shown with (a) raw Worldview-2 imagery, and as mapped with (b) pan-sharpened high-resolution (PSHR) imagery, (c) matched filtering (MF) Landsat, and (d) the Global Surface Water (GSW) monthly Landsat product. The high-resolution imagery can map narrow interactions missed by Landsat (yellow circle), whereas the MF Landsat sometimes detected interactions missed by the GSW Landsat (green circle). MF Landsat can also falsely detect interactions, such as across roads, where a culvert may occur but is not visible (purple circle). Copyright 2012 Digital Globe, Next View License.

Figure 10.

A comparison of Barnes Lake, North Dakota as (a) seen by high-resolution imagery, (b) mapped by pan-sharpened high-resolution (PSHR, 0.5 m) imagery with National Wetlands Inventory (NWI) polygons shown within the continuous lake extent, (c) seen by Landsat, (d) mapped by matched filtering (MF, 30 m) Landsat and the Landsat Global Surface Water (GSW, 30 m) monthly product. Only surface water continuous with Barnes Lake is shown. The GSW missed the surface connection between Barnes Lake and the wetlands north of it. Key interactions detected or missed are shown in the yellow and green circles. Copyright 2011 Digital Globe, Next View License.

Figure 11. Examples of potential conveyances between wetlands that showed visual evidence of occasional to intermittent surface-water presence, but were dry or not continuously wet at the time of the image collection. Copyright 2004 and 2011 Digital Globe, Next View License.

Table 1.

Images utilised in the analysis by site and wetness index for the month preceding the image dates. A total of 19 high-resolution images were processed relative to 13 Landsat images and 13 Global Surface Water (GSW) monthly product rasters. TM: Thematic Mapper, ETM+: Enhanced Thematic Mapper plus, OLI: Operational Land Imager, PHDI: Palmer Hydrological Drought Index, SP24: 24 month standardized precipitation index.

Site	High-Resolution Image Date	Image Count	Satellite	Landsat Image Date	Satellite	Landsat path/row	Gap (Days)	GSW (month)	PHDI	SP24
Cottonwood Lake study area wetlands	29 August 2011	1	Worldview-2	7 September 2011	TM	p31r27	9	Sept 2011	9.93	2.51
	24 July 2015	1	Worldview-2	August 2015	OLI	p31r27	7	Aug 2015	3.76	1.47
Waubay National Wildlife Refuge wetlands	10 October 2004	1	QuickBird-2	29 September 2004	TM	p29r29	-11	Sept 2004	3.53	0.27
	30 April 2012	1	Worldview-2	3 April 2012	ETM+	p29r29	-27	Apr 2012	2.35	1.15
Waubay National Wildlife Refuge lakes	7 June 2012	3	Worldview-2	1 July 2012	ETM+	p29r29	24	Jun 2012	1.75	0.99
	8 June 2015	3	Worldview-2	18 July 2015	OLI	p29r29	40	Jul 2015	1.76	0.25
Barnes Lake	30 July 2011	2	Worldview-2	5 July 2011	TM	p31r27	-25	Jul 2011	8.91	2.20
	30 May 2015	2	GeoEye-1	14 June 2015	OLI	p31r27	15	Jun 2015	3.62	1.24
Horseshoe Lakes	15 April 2015	1	Worldview-2	11 April 2015	OLI	p31r27	-4	Apr 2015	-1.37	0.20
Shyenne River	21 April 2003	1	QuickBird-2	26 April 2003	TM	p31r27	5	Apr 2003	-2.02	-0.56
	15 April 2015	1	Worldview-2	11 April 2015	OLI	p31r27	-4	Apr 2015	-1.37	0.20
Niobrara River	15 August 2006	1	QuickBird-2	16 July 2006	TM	p30r30	-30	Jul 2006	-3.86	-0.07
	30 June 2010	1	Worldview-2	25 June 2010	TM	p30r30	-5	Jun 2006	7.59	2.26

Table 2.

The name, size and location of the lakes analysed per site in the analysis. Lake sizes were calculated using the National Wetlands Inventory lacustrine polygons (USFWS, 2010).

Site and Lake	Size (ha)	Location
Waubay National Wildlife Refuge lakes		
Waubay Lake	1803	45°25'27" N, 97°23'8" W
Spring Lake	361	45°24'45" N, 97°19'30" W
Rush Lake	436	45°20'32" N, 97°21 '56" W
Blue Dog Lake	479	45°21'5" N, 97°17'47" W
Bitter Lake	737	45°16'39" N, 97°19'4" W
Barnes Lake		
Barnes Lake	210	47°15'56" N, 99°16'29" W
Horseshoe Lake		
Horseshoe Lake	219	47°51'14" N, 98°47'31" W
unnamed lake	49	47°49'3" N, 98°49'56" W

Table 3.

The accuracy of the pan-sharpened high-resolution surface-water outputs validated using surface-water level data collected at wetlands within the Cottonwood Lake study area, North Dakota.

Sensor	Image Date	Field Collected Water Level Date	Omission Error (%)	Commission Error (%)	Overall Accuracy (%)	Dice Coefficient (%)	Relative Bias (%)	Water Level Wetland Count	Average wetland size (ha)	Wetland size range (ha)	Wetlands Mapped Count
Worldview-2	29 August 2011	26 August 2011	11	0.0	94.5	94.2	-11	8	4.2	0.3 to 17.6	7
Worldview-2	24 July 2015	27 July 2015	13	1.1	93.0	92.6	-12	8	3.8	0.3 to 16.3	7
Worldview-2	Averaged	Averaged	12	0.6	93.8	93.4	-12	~	~	~	~

Table 4.

A comparison of the accuracy statistics generated when the validation points were randomly sampled across (1) all image extents, (2) lakes only, (3) wetlands only, (4) rivers only, and (5) using field-based water level data from the Cottonwood Lake Study Area. Validation points were generated independently for each of the five separate validation efforts. MF: matched filtered, GSW: Global Surface Water monthly product, n : number of validation points.

Sensor	Validation	n	Omission Error (%)	Commission Error (%)	Overall Accuracy (%)	Dice Coefficient (%)	Relative Bias (%)
MF Landsat	All aquatic systems	12,000	7	1.9	95.6	95.5	-5.2
	Lakes	2,000	3.6	1.7	97.4	97.3	-1.9
	Wetlands	1,600	7.5	4.8	93.9	93.8	-2.9
	Rivers	1,600	64.3	2.4	67.4	52.3	-63.4
	Field water levels	400	22	4.4	87.3	85.9	-18.5
GSW Landsat	All aquatic systems	12,000	15.7	1.4	91.6	90.9	-14.5
	Lakes	2,000	6.4	1.9	95.9	95.8	-4.6
	Wetlands	1,600	14.4	2.4	91.8	91.2	-12.3
	Rivers	1,600	84.3	0.8	57.8	27.2	-84.1
	Field water levels	400	42	0	79.2	73.1	-41.8

Table 5.

Summary of the percent of stream length mapped by stream width and data source. Average stream/river width was determined from the pan-sharpened high-resolution images (PSHR). MF: matched filtering, GSW: Global Surface Water monthly product.

Average wetted width (m)	PSHR (%) Detected	MF Landsat (%) Detected	GSW (%) Detected	MF Landsat relative to PSHR (%)	GSW relative to PSHR (%)	Site	Month, Year (PSHR)
2	7	0	0	-100	-100	Niobrara Tributary	Aug 2006
3	22	0	0	-100	-100	Sheyenne River Tributary	Apr 2003
3	7	0	0	-100	-100	Sheyenne River Tributary	Apr 2003
3	2	0	0	-100	-100	Sheyenne River Tributary	Apr 2003
3	24	5	0	-79	-100	Sheyenne River Tributary	Apr 2003
3	12	1	0	-92	-100	Sheyenne River Tributary	Apr 2003
3	27	0	0	-100	-100	Sheyenne River Tributary	Apr 2015
4	2	0	0	-100	-100	Niobrara Tributary	Jun 2010
4	75	0	0	-100	-100	Niobrara Tributary	Aug 2006
6	54	5	0	-91	-100	Sheyenne River Tributary	Apr 2003
7	56	0	0	-100	-100	Niobrara Tributary	Aug 2006
7	83	0	0	-100	-100	Niobrara Tributary	Jun 2010
8	95	5	0	-95	-100	Niobrara Tributary	Jun 2010
9	55	4	0	-93	-100	Sheyenne River Tributary	Apr 2015
12	66	0	0	-100	-100	Sheyenne River Tributary	Apr 2003
15 (4 to 30)	58	38	4	-34	-93	Niobrara Tributary	Jun 2010
16	92	4	0	-96	-100	Sheyenne River Tributary	Apr 2015
29 (3 to 80)	72	45	36	-38	-50	Sheyenne River Tributary	Apr 2003
33	94	28	5	-70	-95	Sheyenne River	Apr 2015
41	90	56	5	-38	-94	Niobrara Tributary	Jun 2010
45	96	81	29	-16	-70	Sheyenne River	Apr 2003
47	94	97	70	3	-26	Niobrara River	Aug 2006
84	90	93	78	3	-13	Niobrara River	Jun 2010
<10 m	37	1	0	-96	-100	averaged	~
10 to 30 m	72	22	10	-67	-86	averaged	~
31 to 85 m	93	71	37	-23	-60	averaged	~

Table 6.

Wetland metrics across wetland mosaic sites and years, where the year refers to the year the satellite image was collected. Change is presented relative to the pan-sharpened high resolution (PSHR) imagery, as well as for the PSHR imagery relative to the Landsat products. NWI: National Wetlands Inventory, MF: matched filtering, GSW: Global Surface Water monthly product.

Metric	Site	Cottonwood Lake wetlands		Waubay National Wildlife Refuge wetlands		Change relative to PSHR (%)	PSHR relative to Landsat(%)
	Source	2011	2015	2004	2012	all	all
Surface-water extent. (ha)	PSHR (0.5 m)	3330.5	3274.7	3258.9	4009.8	~	~
	MF Landsat (30 m)	3391.8	3089.4	3678.4	3826.5	0.8	−0.8
	GSW Landsat (30 m)	2596.1	3014.8	2589.7	2775.2	−20.9	26.4
	NWI ^a	3085	4567	1858	2139	~	~
NWI wetlands detected. (count)	PSHR (0.5 m)	1803	1296	735	1106	~	~
	MF Landsat (30 m)	844	1038	505	819	−35.1	54.1
	GSW Landsat (30 m)	565	719	376	621	−53.8	116.6
NWI wetland/wetland interactions. (count)	PSHR (0.5 m)	232	230	257	511	~	~
	MF Landsat (30 m)	236	223	272	424	−6.1	6.5
	GSW Landsat (30 m)	125	164	103	252	−47.6	91.0
Clusters of NWI wetlands. (count)	PSHR (0.5 m)	68	76	80	143	~	~
	MF Landsat (30 m)	70	93	84	120	0.0	0.0
	GSW Landsat (30 m)	40	63	35	88	−38.4	62.4

^aAs the NWI wetland dataset can be outdated (generated 1977–2016 depending on the location), wetlands may or may not still be present and may or may not contain water at the time of the image collection.

Table 7.

Continuous lake extent and wetlands detected within lake extent by site and year. Wetland/lake surface water interactions occur when a lake expands, subsuming a wetland, or a wetland fills and spills into a lake. Change is presented relative to the pan-sharpened high resolution (PSHR) outputs, as well as for the PSHR outputs relative to the Landsat products. NWI: National Wetlands Inventory, MF: matched filtering, GSW: Global Surface Water monthly product.

Metrics	Site	Waubay National Wildlife Refuge lakes		Barnes Lake		Horseshoe Lakes	Change relative to PSHR (%)	PSHR relative to Landsat (%)
	Year	2012	2015	2011	2015	2015	all	all
NWI wetlands detected within lake surface-water extent. (count)	PSHR (0.5 m)	557	618	127	79	73	~	~
	MF Landsat (30 m)	562	618	107	75	64	1.9	2.0
	GSW Landsat (30 m)	263 ^a	538	9	61	58	-36.1	56.5
Continuous lake surface-water extent (ha)	PSHR (0.5 m)	12,595.9	14,510.8	1171.8	1044.5	886.5	~	~
	MF Landsat (30 m)	12,776.7	14,538.7	1139.0	1003.2	843.6	0.3	-0.3
	GSW Landsat (30 m)	5565.0 ^a	13,067.7	205.0	930.8	741.6	-32.1 (-15.2 ^b)	47.3 (18.0 ^b)

^aProduct affected by the Scan-Line Corrector off (SLC-off) error.

^bPercent change in continuous lake surface-water extent relative to PSHR outputs, excluding the Wildlife Refuge lakes (2012).