Hydrology and Earth System Sciences



### 1 Wetlands inform how climate extremes influence surface water expansion and contraction

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- 19 Abstract

20 Effective monitoring and prediction of flood and drought events requires an improved

- understanding of how and why surface-water expansion and contraction in response to climate
- varies across space. This paper sought to (1) quantify how interannual patterns of surface-water
- 23 expansion and contraction vary spatially across the Prairie Pothole Region (PPR) and adjacent
- 24 Northern Prairie (NP) in the United States, and (2) explore how landscape characteristics
- 25 influence the relationship between climate inputs and surface-water dynamics. Due to differences
- 26 in glacial history, the PPR and NP show distinct patterns in regards to drainage development and
- 27 wetland density, together providing a diversity of conditions to examine surface-water dynamics.
- 28 We used Landsat imagery to characterize variability in surface-water extent across eleven
- 29 Landsat path/rows representing the PPR and NP (images spanned 1985-2015). The PPR not only
- 30 experienced a 2.6-fold greater surface-water extent under median conditions relative to the NP,
- but also showed a 3.4-fold greater change in surface-water extent between drought and deluge
- 32 conditions. The relationship between surface-water extent and accumulated water availability





33 (precipitation minus potential evapotranspiration) was quantified per watershed and statistically related to variables representing hydrology-related landscape characteristics (e.g., infiltration 34 35 capacity, surface storage capacity, stream density). To investigate the influence streamconnectivity has on the rate at which surface water leaves a given location, we modeled stream-36 connected and stream-disconnected surface water separately. Stream-connected surface water 37 showed a greater expansion with wetter climatic conditions in landscapes with greater total 38 39 wetland area. Disconnected surface water showed a greater expansion with wetter climatic conditions in landscapes with higher wetland density, lower infiltration and less anthropogenic 40 drainage. From these findings, we can expect that shifts in precipitation and evaporative demand 41 will have uneven effects on surface-water quantity. Accurate predictions regarding the effect of 42 climate change on surface-water quantity will require consideration of hydrology-related 43 landscape characteristics including wetlands. 44 45 46 **Keywords** Drought, evapotranspiration, Landsat, prairie pothole region, precipitation, surface water 47 48 **1. Introduction** 49 50 Surface-water dynamics have strong implications for ecosystem functioning and human 51 land use including biogeochemical balances (Hoffmann et al., 2009), species distribution (Boschilia et al., 2008; Calhoun et al., 2017), hydrologic connectivity (Heiler et al., 1995; 52 Pringle, 2001)), and agricultural productivity (Mokrech et al., 2008; Gornall et al., 2010). Yet 53 54 natural variability in surface-water extent poses a basic challenge to gathering timely, accurate information (Poff et al., 1997; Beeri and Phillips, 2007). While satellite imagery can be used to 55





56	map variability in surface-water extent over time, predicting future changes in surface-water
57	extent (e.g., in response to changes in climate, land use, or natural disasters) requires improving
58	our understanding of how the landscape influences surface-water extent over time and space. The
59	relative importance of hydrologic processes and flowpaths across a landscape (e.g., surface
60	storage, infiltration, evapotranspiration, runoff) can be expected to influence the timing, duration
61	and extent of surface water for a given location (Euliss and Mushet, 1996; LaBaugh et al., 1996,
62	van der Kamp et al., 1999)
63	Winter (2001) presented the concept of hydrologic landscapes as a means to classify
64	landscape units based on their hydrologic attributes (land-surface form, geology and climate).
65	These attributes, it is argued, could then be used to predict the partitioning of water into storage,
66	infiltration, evapotranspiration and runoff (Wagener et al., 2007). In many landscapes storage is
67	minimal and when rainfall intensity is greater than both the rate of soil infiltration and the soil
68	moisture deficit, runoff via overland and subsurface flows will dominate, contributing to
69	increased stream discharge (Eamus et al., 2006). These landscapes could be described as
70	exhibiting a low potential for surface-water expansion. Alternatively, in landscapes with low
71	topographic gradients and poorly developed drainage networks, runoff events rarely deplete
72	available surface storage, meaning that although stream discharge may elevate, much of the
73	surplus water remains as surface water (Shaw et al., 2012; Kuppel et al., 2015). These landscapes
74	show a high potential for surface-water expansion with evapotranspiration often the primary
75	mechanism for water loss (Winter and Rosenberry, 1998). Landscapes with a tendency to
76	accumulate surface-water are relatively common across the globe and include former glacial
77	landscapes including the Prairie Pothole Region (PPR) (Sass and Creed, 2008; Shaw et al.,
78	2012), and parts of China (Yao et al., 2007) and Russia (Stokes et al., 2007), permafrost regions





79	(Smith et al., 2007), as well as low gradient landscapes including the Argentine Pampas (Kuppel
80	et al., 2015); the Pantanal in Brazil (Hamilton, 2002), and the Orinoco Llanos in Columbia and
81	Venezuela (Hamilton, 2004). Although such landscapes have previously been shown to
82	experience surface-water expansion in response to increased precipitation (Huang et al., 2011;
83	Kuppel et al., 2015; Vanderhoof et al., 2016) or melting ice (Stokes et al., 2007; Yao et al.,
84	2007), we are unaware of studies that have explicitly compared surface-water expansion and
85	contraction between landscapes of differing surface-water expansion potential.
86	The PPR and adjacent Northern Prairie (NP), which span the upper mid-west of the
87	United States, occur within and beyond the last glacial maximum, respectively, and together
88	represent a range in the potential for surface-water expansion. The PPR is characterized by a
89	high density of depressional wetland and lake features (Zhang et al., 2009), a relic of glacial
90	retreat (Flint, 1971). Most wetlands are relatively small ( $< 0.5$ ha) depressions, underlain by
91	glacial till with low permeability, and occur within a landscape matrix of natural grassland and
92	agriculture (Winter and Rosenberry, 1995; Zhang et al., 2009; Cohen et al., 2016). This is in
93	contrast to the adjacent NP such as the Northwestern Great Plains (Montana, western North and
94	South Dakota) and the Central Irregular Plains (southern Iowa and northern Missouri), which
95	lack the high density of small wetlands and show a well-developed drainage network due to its
96	occurrence outside of the last maximum glacial extent (USGS, 2013). The NP and PPR are also
97	characterized by substantial spatial and interannual variability in air temperature and
98	precipitation (Bryson and Hare 1974). Variations in temperature and moisture content of
99	competing air masses results in a strong north-south temperature and east-west precipitation
100	gradient. The precipitation-evaporation deficit is least in the east (i.e., Minnesota and Iowa), and
101	increases to the west (i.e., Montana) (Kantrud et al., 1989; Millet et al., 2009). This variability in





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102	climate has a strong influence on water levels across the region. In the PPR in spring, wetland
103	depressions receive water from both precipitation and snowmelt. In the summer, water level is
104	controlled by direct precipitation, evaporation and wetland vegetation transpiration (Winter and
105	Rosenberry, 1995; LaBaugh et al., 1998; Carroll et al., 2005), with evapotranspiration typically
106	dominating water loss (Rosenberry et al., 2004).
107	Monitoring variation in water levels across the PPR has been of high interest as it is a key
108	factor in flood abatement, water quality, biodiversity, carbon management and aquifer recharge
109	(Gleason et al., 2008). Water level data at Devils Lake, North Dakota, for example, have been
110	collected as far back as 1867 and provide a regional indicator of hydrological conditions (Wiche,
111	1996; LaBaugh et al., 1996). Efforts have been expanded to map interannual changes in surface-
112	water extent across the PPR at a landscape scale using remotely sensed imagery (Kahara et al.,
113	2009; Niemuth et al., 2010; Vanderhoof et al., 2016). However, while substantial interannual
114	variation in water level has been documented across the PPR (Huang et al., 2011; Vanderhoof et
115	al., 2016), and primarily attributed to interannual variation in temperature and precipitation
116	(Johnson et al., 2005; Zhang et al., 2009), such surface-water patterns have to date been
117	minimally characterized for the remainder of the NP. In addition to interannual patterns of
118	temperature and precipitation, we would also expect that surface-water extent will depend on
119	landscape parameters such as infiltration capacity, storage capacity, and drainage characteristics
120	(Euliss and Mushet, 1996; LaBaugh et al., 1996; van der Kamp et al., 1999). Spatial models
121	incorporating some of these factors can provide additional insights into the risk of flood and
122	drought events across the PPR (Niemuth et al., 2010).
123	The PPR, in conjunction with adjacent NP, provides an ideal physiographic example in

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which to analyze the influence of landscape characteristics on surface-water expansion and





125	contraction. Although the interaction between water level and climate has been studied
126	extensively at select locations within the PPR (e.g., Cottonwood Lake) (Winter and Rosenberry,
127	1998; Huang et al. 2011), minimal research has sought to understand spatial variability in the
128	relationship between climate and surface-water extent. Our research questions addressed in this
129	study are:
130	(1) How do interannual patterns of surface-water expansion and contraction vary
131	spatially across the Prairie Pothole Region and adjacent Northern Prairie of the
132	United States?
133	(2) How do landscape characteristics influence the relationship between climate inputs
134	and surface-water dynamics?
135	The successful exploration of this spatial patterning and landscape-scale statistical functions will
136	inform hydrologic/hydraulic and biogeochemical modeling and has implications for
137	biodiversity/habitat modeling and management (e.g., Allen et al., 2016; Golden et al., 2017)
138	2. Methods
139	As detailed below, we used Landsat imagery to map surface-water extent under dry,
140	average, and wet conditions across portions of the PPR and adjacent NP. We compared the
141	expansion and contraction of surface-water extent between the PPR and adjacent NP. As stream-
142	connected surface water can leave a location easily as stream flow, stream-connected and
143	disconnected surface water were analyzed separately. We then used a two-level modeling
144	approach to investigate the influence of landscape variables on surface-water dynamics. In the
145	first stage, surface-water extent per watershed was statistically related to accumulated water
146	availability, defined as precipitation minus potential evapotranspiration. This first stage produced
147	the dependent variable for the second model, the slope of the relationship between surface-water





148	extent and climate inputs per hydrological unit (a watershed) or the Surface Water Climate
149	Response (SWCR). The SWCR was then regressed against independent variables representing
150	landscape characteristics (e.g., infiltration capacity, surface storage capacity, stream density,
151	long-term climate normals). This approach allowed us to explore what landscape characteristics
152	drive spatial variability in the relationship between surface-water extent and climate.
153	
154	2.1 Study Area
155	Our study area consisted of eleven Landsat path/rows (total area = $308,439$ km <sup>2</sup> ) in the
156	U.S. portion of the PPR and adjacent NP (Figure 1). The PPR across North and South Dakota,
157	western Minnesota, northern Iowa and northern Nebraska, is dominated by the North and
158	Northwest Glaciated Plains. This ecoregion is characterized by landscape features formed during
159	its recent glacial history. Drift plains, large glacial lake basins and shallow river valleys support
160	row crop agriculture. Grasslands and livestock grazing dominate areas where glaciers left
161	deposits of uneven glacial till (Sayler et al., 2015). The PPR is dominated by cultivated crops
162	(59%), herbaceous (18%) and hay/pasture (10%) (Homer et al., 2015). Adjacent to the PPR, the
163	Northwestern Great Plains, across western North and South Dakota, is a semiarid unglaciated
164	plain which tends to have shallow soils with a clay texture not conducive to growing crops and
165	instead dominated by livestock grazing across grasslands (Sayler et al., 2015). To the southeast
166	of the North Glaciated Plains lies the Western Corn Belt and the Central Irregular Plains in Iowa
167	and Nebraska. Glacial till forms the parent material for most of the soil in Western Corn Belt and
168	the northern part of the Central Irregular Plains, within the study area. Level and gently rolling
169	hills and fertile soils support agriculture (Sayler et al., 2015). The NP is dominated by
170	herbaceous land cover (47%) with cultivated crops (28%) and hay/pasture (9%) is also common





171	(Homer et al., 2015). Using the precipitation averages (1981-2010) defined by the Parameter-
172	elevation Regressions on Independent Slopes Model (PRISM, Daly et al., 2008), the PPR study
173	area receives 6% more precipitation on average than the NP study area (626 mm yr <sup>-1</sup> relative to
174	592 mm yr <sup>-1</sup> , respectively) and 1.5% less evaporative demand or potential evapotranspiration
175	(PET) (603 mm yr <sup>-1</sup> relative to 594 mm yr <sup>-1</sup> , respectively). These differences were not found to
176	be statistically different using the Wilcoxon rank sum test.
177	Our regression analysis used eight-digit Hydrologic Unit Codes (HUC8s; USDA NRCS,
178	2015) as the unit of analysis (n=150) across all eleven Landsat path/rows (Figure 1). HUC8s
179	were used instead of smaller watersheds such as HUC10s or HUC12s to ensure that patterns in
180	surface-water expansion and contraction represented landscape patterns, not individual or small
181	groups of water features. HUC8s that occurred at the edge of a Landsat path/row with an area of
182	< 50 ha were excluded from further regression analysis to limit the inclusion of incompletely
183	characterized watersheds. The threshold of 50 ha was selected as it was a natural break in the
184	distribution of HUC8 sizes. Patterns of surface-water expansion and contraction were compared
185	between the PPR and NP. We note that one path/row (p37r26) in northern Montana was
186	technically within the most western section of the PPR, but was found to behave dissimilarly
187	from the PPR and similarly to the NP in terms of both its landscape characteristics (e.g., stream
188	density, wetland density) and surface-water expansion and contraction. Because of this, p37r26
189	was included in the adjacent NP for analyses where findings were organized by PPR and NP.
190	

191 2.2 Landsat Image Processing

192 2.2.1 Path-Row and Image Selection





193	Surface-water extent was mapped for a series of images across 11 Landsat path/rows
194	(Figure 1). These path/rows were selected to represent the PPR and adjacent NP and were
195	intentionally selected to represent a range of ecoregions, climate conditions (west to east and
196	north to south) and densities of wetlands and streams. Snow-free images (acquired
197	approximately from April through October) containing less than 10% cloud cover from the
198	Landsat 4-5 TM, Landsat 7 ETM+ (prior to failure of the scan-line corrector in 2003) and
199	Landsat 8 OLI sensors were selected between 1985 and 2015. The number of images processed
200	within each path/row averaged 14 (range: 9 to 17 acceptable images) and were intentionally
201	selected to document interannual variability in surface-water extent, by selecting images from
202	wet, average and dry years (Table 1). The terms "wet", "average" and "dry" were defined in
203	reference to local norms, using the Palmer Hydrological Drought Index (PHDI) and the 12-
204	month Standardized Precipitation Index (SP12) (NOAA, NCDC, 2014). The range of conditions
205	captured by the time series within each path/row in relation to the historical climate conditions
206	(1895-2015) are shown in Table 1. The PHDI is based on a monthly water balance accounting
207	approach that considers precipitation, evapotranspiration, runoff and soil moisture. The indices
208	rely on weather station data and are interpolated at 5 km (NOAA NCDC, 2014). A complete list
209	of images included in the analysis is presented in the Appendix (Table A1).
210	

211 2.2.2 Image Processing

Images were atmospherically corrected and converted to surface reflectance values using the Landsat Ecosystem Disturbance Adaptive Processing System (Masek et al., 2006). A minimum noise fraction transformation was applied to reduce within-image noise (Green et al., 1988). The per-pixel water fraction was estimated using the Matched Filtering algorithm, a





216	partial unmixing method in the ENVI software package (Exelis Visual Information Solutions,
217	Inc, Herndon, Va) (Turin, 1960; Vanderhoof et al., 2016). This algorithm is trained on a water
218	spectral signature, which was derived from open-water polygons manually selected within each
219	path/row, resulting in a water signature specific to each image. The water fraction output was
220	linearly stretched to maximize our ability to separate water from non-water. CFmask, a quality
221	control layer provided with Landsat images, was used to mask out clouds and cloud shadows
222	(Zhu and Woodcock, 2014), while the National Land Cover Database (NLCD) (2011) was used
223	to mask out impervious surfaces, defined as low, medium and high density development (Homer
224	et al., 2015), which can show spectral confusion with surface water. Each surface-water image
225	was visually inspected for quality using visual interpretation as well as ancillary datasets (e.g.,
226	National Agricultural Imagery Program (NAIP) imagery, National Wetland Inventory (NWI)
227	dataset (USFWS, 2010)). Select images were removed or edited primarily due to spectral
228	confusion between water and bare rock or shadowed vegetation.
229	
230	2.2.3 Surface-Water Extent Validation
231	The surface-water extent maps were validated using 1-m resolution NAIP imagery

231 The surface-water extent maps were validated using 1-m resolution NAIP imagery. Landsat images were selected for validation based on the temporal coincidence of the Landsat 232 and NAIP imagery collections (Table 2). Because terrestrial surface water is a relatively rare 233 234 cover type, it is difficult to generate enough inundated reference points through a simple randompoint generation. Therefore, random points were generated in reference to NWI polygons 235 236 overlapping with the NAIP and Landsat imagery. Points were then visually identified as inundated or non-inundated using the NAIP imagery. To account for the scale difference 237 between a random point and a 900 m<sup>2</sup> Landsat pixel, the Landsat pixel boundaries for each 238





239	random point were identified. The point was classified as the majority class (inundated or non-
240	inundated) identified by NAIP within the Landsat pixel boundary surrounding each random
241	point. Reference points were generated per Landsat/NAIP pair (500 or 1000), with the number of
242	reference points varying depending on the amount of NAIP imagery available within the Landsat
243	path/row extent, and the number of random points that occurred within Landsat NA pixels.
244	Metrics presented included overall accuracy, omission error, commission error, dice coefficient,
245	and relative bias. Omission and commission errors were calculated for the category "water". The
246	dice coefficient is the conditional probability that if one classifier (product or reference data)
247	identifies a pixel as water, the other one will as well, and therefore integrates omission and
248	commission errors (Fleiss, 1981; Forbes, 1995). The relative bias provides the proportion that
249	water is under (negative) or overestimated (positive).
250	The Landsat per-pixel fraction water was binned into inundated ( $\geq 0.3$ ) and non-
251	inundated ( $< 0.3$ ) classes. This threshold was selected as it best balanced errors of omission and
252	commission. Overall accuracy for the Landsat surface-water maps across the 11 path/rows was
253	93.9% with errors of omission for surface water averaging 8.5% and errors of commission for
254	surface water averaging 8.2% (Table 3). The surface-water maps showed no relative bias and a
255	dice coefficient of 92%. Errors of omission and commission can be primarily attributed to mixed
256	Landsat pixels occurring over small wetlands (a few pixels in size) or at the edge of larger
257	wetlands or open water features. In some images parts of or entire agricultural fields were
258	classified as water. It is common in both the spring months, when crops need to be planted, and
259	fall months, when crops are being harvested, for fields to experience wet conditions (Fausey et
260	al., 1987; King et al., 2014). In addition, poorly drained soil is common across this region
261	(Skaggs et al., 1994) and wetland depressions often occur within agricultural fields.





262	Consequently, subsurface tile drainage has become increasingly popular across the region to
263	speed up the removal of excess soil water (Blann et al., 2009). It is often unclear to what extent
264	surface-water mapped within agricultural fields represents historical or current wetlands, poorly
265	drained fields, or misclassified pixels. Lastly, a close match in acquisition date between the
266	Landsat and NAIP images is essential for the NAIP imagery to accurately represent ground
267	conditions. Variability in the date match can be considered one potential source of error, as the
268	occurrence of a rain event or seasonal variability can change surface-water conditions over even
269	short time periods.

270

### 271 2.3 Surface-Water Extent Analysis

Surface-water abundance (ha km<sup>-2</sup>) was calculated per HUC8 with HUC8 area being 272 273 adjusted for each image based on the abundance of not applicable (NA) pixels (e.g., cloud cover, 274 cloud shadow) in each image. We used the high-resolution National Hydrography Dataset (NHD, 1:24,000) to classify surface water as (1) continuous connected with the stream network, or (2) 275 disconnected from the stream network. The NHD line dataset was buffered by 14 m, the reported 276 277 digital horizontal accuracy of the dataset (USGS, 2000) and NHD area was added to account for the width of large rivers. Surface-water polygons that intersected the stream network in a given 278 image were classified as continuously connected water (CCW). Surface-water polygons that did 279 280 not intersect the stream network in a given image were classified as discontinuous water (DCW) 281 or discontinuous from the stream network. We acknowledge that the NHD is known to be 282 incomplete (e.g., lacking short and ephemeral stream lines) and that some stream lines within the 283 NHD are disconnected from downstream waters (Heine et al., 2004). However, the NHD is the most complete nationally-available stream dataset. 284





285	Processed images within each path/row were ranked from least-to-most amount of
286	surface water per area. Median condition was defined as the image or two images representing
287	the median amount of surface-water extent, estimated from all images within a path/row.
288	Drought and deluge conditions were defined as the average of the two end-member images
289	showing the least and most amount of total surface-water extent for each path/row, respectively.
290	Surface-water extent was then summed across the PPR and NP path/rows and divided by the
291	total area to calculate the hectares of surface-water extent per $\mathrm{km}^2$ for each region. The NP
292	portion of path 27, row 30 (p27r30) and p30r30 were deleted, as was the PPR portion of p26r30
293	to avoid double counting overlapped path/rows.
294	
295	2.4 Stage One – Derivation of the Surface Water Climate Variable (SWCR)
296	In stage one, surface-water extent in each HUC8 was related, using linear regression, to
297	water availability, defined as precipitation minus PET summed over a time interval. Water

availability provided an estimate of the amount of water in each watershed available to either (1)

runoff, (2) infiltrate to shallow or deep groundwater sources, or (3) be stored as surface-water.

300 Surface water was again partitioned into CCW and DCW using its spatial relationship to the

301 NHD. Precipitation data were compiled using the Parameter-elevation Regressions on

302 Independent Slopes Model (PRISM, Daly et al., 2008). PET, or the atmospheric demand for

303 evaporation and transpiration in the absence of water limitations, which can be expected over

304 open surface water, was compiled using gridded surface meteorological data PRISM and the

- North American Land Data Assimilation System Phase 2 (Abatzoglou et al., 2011). PET was
- 306 calculated using the Penman-Monteith equation that required inputs of minimum and maximum
- 307 temperature, daily average dewpoint temperature (equivalently, vapor pressure or vapor pressure





308	deficit), wind speed and downward shortwave radiation (Abatzoglou et al., 2011, Mitchel et al.,
309	2004). The datasets were resampled to 125 m using cubic convolution and summarized for each
310	HUC8. Water availability was summed for a series of monthly periods preceding each image
311	date (3, 6, 9, 12, 18, 24, 30 and 36 months) to identify the accumulation period for which the
312	greatest number of HUC8's showed a significant (p<0.05) slope between water availability and
313	surface-water extent. This logic was meant to reduce the probability that a zero slope resulted
314	from surface water responding more strongly to climate drivers at a different time interval. This
315	first stage produced surface water climate response (SWCR), our dependent variables for stage 2,
316	i.e., the slope of the relationship between CCW and DCW surface-water extent to accumulated
317	water availability (Figure 2). The slope or stage 2 dependent variable is referred to as the surface
318	water climate response (SWCR) from this point forward.
319	Cloud cover makes it challenging to restrict analysis of Landsat imagery to a specific
319 320	Cloud cover makes it challenging to restrict analysis of Landsat imagery to a specific season, while including imagery that covers more than one season potentially conflates seasonal
320	season, while including imagery that covers more than one season potentially conflates seasonal
320 321	season, while including imagery that covers more than one season potentially conflates seasonal surface-water dynamics with interannual surface-water dynamics. The influence of seasonal
320 321 322	season, while including imagery that covers more than one season potentially conflates seasonal surface-water dynamics with interannual surface-water dynamics. The influence of seasonal change in surface-water extent within our analysis contributed to the uncertainty (primarily
320 321 322 323	season, while including imagery that covers more than one season potentially conflates seasonal surface-water dynamics with interannual surface-water dynamics. The influence of seasonal change in surface-water extent within our analysis contributed to the uncertainty (primarily through sampling error) in the SWCR. For example, if we included an image from June 1993 and
320 321 322 323 324	season, while including imagery that covers more than one season potentially conflates seasonal surface-water dynamics with interannual surface-water dynamics. The influence of seasonal change in surface-water extent within our analysis contributed to the uncertainty (primarily through sampling error) in the SWCR. For example, if we included an image from June 1993 and one from August 1993 and related both images to the last nine months of precipitation and PET
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<ul> <li>320</li> <li>321</li> <li>322</li> <li>323</li> <li>324</li> <li>325</li> <li>326</li> </ul>	season, while including imagery that covers more than one season potentially conflates seasonal surface-water dynamics with interannual surface-water dynamics. The influence of seasonal change in surface-water extent within our analysis contributed to the uncertainty (primarily through sampling error) in the SWCR. For example, if we included an image from June 1993 and one from August 1993 and related both images to the last nine months of precipitation and PET (Sept 1992 - May 1993 and November 1992 – July 1993, respectively), greater seasonal dynamics or variation in surface-water extent between the two dates can be expected to show up





described below in the Stage 2 Analysis (Section 2.6), we can, to the extent possible, account for

331 seasonally induced variation in surface-water extent.

332

#### 333 2.5 Landscape Variables for Stage 2 Analysis

The independent variables summarized for each HUC8 and included in the analysis were

selected to characterize mechanisms through which water can leave the landscape (e.g.,

infiltration, runoff, tile drainage), mechanisms through which water can remain and expand on

the landscape (e.g., wetland density, wetland size, topography), as well as other potential

338 influences on surface water dynamics (e.g., climate norms, land cover). The National Wetland

Inventory (USFWS, 2010) and NHD stream dataset (USGS, 2013) were used to calculate

340 wetland and stream characteristics including stream density, wetland count and areal density, and

341 proportion of total wetland area attributed to large (>8 ha) features. A threshold of 8 hectares was

selected as this is the size threshold used by USFWS to define a lacustrine system (Cowardin et

al., 1979). We do not refer to these features as lakes, however, as water depth and associated

vegetation are also important features to defining lacustrine systems, and were not evaluated. We

345 did not include distance variables, which were previously found to be highly correlated with

simpler variables already in the analyses: mean wetland-to-wetland distance was previously

found to be highly correlated with wetland density (r = -0.95, p < 0.01) and mean wetland-to-

348 stream distance highly correlated with stream density (r = 0.88, p<0.01) (Vanderhoof et al.,

349 2017). Surface topography can influence the capacity for surface water to expand and was

350 quantified as the weighted averaged slope gradient, as defined by the U.S. Department of

351 Agriculture's Soil Survey Geographic (SSURGO) Database (Soil Survey Staff, 2017).

352 Topographic Wetness Index was not included because of the relative weakness of such indices in





353	landscapes with little relief (e.g., Schmidt and Persson, 2003) and the data intensive nature of
354	calculating TWI with a 10 m DEM across such a large study area. Additional variables derived
355	from the SSURGO database to characterize infiltration capacity include available water storage
356	(0 - 150 cm), annual minimum depth to water table, and saturated hydraulic conductivity (Ksat).
357	Human influence was quantified as the abundance of agricultural activities, or the percent of
358	each HUC8 classified as agriculture, defined as the NLCD (2011) cover categories hay/pasture
359	and row crop. Anthropogenic modifications to drainage systems, or the percent land cover
360	artificially drained, was estimated as the percent of each HUC8 where row crop cover type
361	(NLCD 2011) and very poorly drained or poorly drained soils as defined by the National
362	Resources Conservation Service's SSURGO database were collocated following Christensen et
363	al., (2013). The climate normals per HUC8 (1989-2013) were calculated to represent the Landsat
364	image range. The precipitation averages are provided as part of the PRISM dataset (Daly et al.,
365	2008). PET was calculated as a function of monthly mean PRISM temperature and day length
366	following Hamon (1961). The Moisture Index (MI) was calculated as the ratio of precipitation
367	and PET where, if PET exceeded precipitation, $MI = precipitation/PET - 1$ , and if precipitation
368	exceed or equaled PET, then $MI = 1 = PET/precipitation$ . Values range from -1 (dry) to 1 (wet)
369	(Willmott and Feddema, 1992; Feddema, 2005). The climate averages were resampled to 1 km
370	from 4 km using inverse-distance weighting, prior to being averaged per HUC8. The distribution
371	of values within each of the independent variables are shown in Table 4. Spearman rank
372	correlations with a Bonferroni correction (Dunn, 1961) were calculated for the independent
373	variables (Table 5).
27/	

374

# 375 2.6 Stage 2 - Analysis - Landscape Mechanisms Explaining Variability in SWCR





376 In stage two, CCW and DCW SWCRs, or the slope of the relationship between CCW and 377 DCW and accumulated water availability, were related to landscape variables using feasible 378 generalized least-squares (FGLS) regression, with HUC8s (n=150) as the unit of analysis. FGLS 379 allowed us to estimate the heteroscedastic structure of the residuals (Lewis and Linzer, 2005) and has been previously applied within landscape ecology contexts (e.g., Acharya, 2000; Villalobos-380 Jimenéz and Hassall, 2017). The SWCRs were found to be significant for the largest number of 381 382 HUC8s using a 9-month period of accumulation for both CCW and DCW, which was therefore 383 used as the accumulation period for further analyses (Table 6). The SWCRs were found to be spatially autocorrelated using Global Moran's I (spatial relationship conceptualized using inverse 384 385 distance) (DCW SWCR, 9 months, z-score=7.8, p<0.01, CCW SWCR, 9 month, z-score=4.1, p<0.01), violating the assumption of independence between samples. To account for spatial 386 autocorrelation in the SWCRs, we calculated an autocovariate in ArcGIS 10.3, Geostatistical 387 388 Analyst (ESRI, Redmond CA) which uses adjacent HUC8s to create a neighbor value. By 389 including a spatial autocovariate in the ordinary least-squares (OLS) regression model, we controlled for how much the response variable reflected response values of adjacent HUCs, 390 391 before identifying additional significant explanatory variables (Dormann et al., 2007; Betts et al., 2009). The autocovariate was automatically retained while only significant independent variables 392 393 (p<0.05) were additionally retained. The dependent variable was normalized using a Box-Cox 394 power transformation (R package MASS, Venables and Ripley, 2002). Multicollinearity was 395 formally assessed using the regression collinearity diagnostics described by Belsley et al. (1980) and implemented in the R package perturb (Hendrickx, 2012). Collinearity may affect parameter 396 397 estimation when a condition index greater than 10 is associated with variance decomposition





proportions greater than 0.5 for two or more explanatory variables (Belsley, 1991). Both models

399 complied with collinearity requirements.

400 Having an estimated dependent variable (e.g., SWCR) does not necessarily present a problem for a regression analysis, but we must recognize that the regression model error term 401 contains two components: (1) the expected random error resulting from sources of variation not 402 accounted for in the model, and (2) the difference between the true value of the dependent 403 variable and the estimated value (sampling error). In this study, the uncertainty around the 404 405 dependent variable (SWCR) was not constant across observations. Instead, the dependent variable showed a strong positive correlation with its standard error (DCW SWCR,  $R^2 = 0.59$ , 406 p<0.05; CCW SWCR,  $R^2 = 0.70$ , p<0.05) (Figure 3). FGLS allowed us to estimate both 407 components of the error. To do so, we: (1) calculated the logarithm of squared residuals from the 408 OLS model, (2) regressed the log-residuals on the independent variables included in the OLS 409 410 model, (3) calculated the exponential of fitted values from that regression, which estimates the variance of the regression residual that is not due to sampling of the dependent variable, z, and 411 (4) estimated the basic model again now including weights  $(1 z^{-1})$  (Hanushek, 1974; Lewis and 412 413 Linzer, 2005). We found the final model residuals to be random using the studentized Breusch-Pagan test (Breusch and Pagan, 1979). 414 To help add confidence regarding which landscape variables were more or less important, 415 416 we also fit random forest models in R using the package randomForest (Liaw and Wiener, 2015). 417 The random forests were run with the SWCRs as the dependent variable and landscape characteristics as independent variables. We derived 500 binary trees or bootstrap iterations 418 419 using out of bag (OOB) samples (70% of samples to train and 30% of samples to validate). Variable importance was calculated as the change in node impurity (i.e., Gini importance). 420





421	Random forest models are generally insensitive to collinearity among metrics, however the

- 422 inclusion of correlated variables can deflate variable importance as well as the overall variation
- 423 explained by the model (Murphy et al., 2010). We implemented random forest model selection to
- select the smallest number of non-redundant variables (varSelRF R package) (Murphy et al.,
- 425 2010).
- 426
- 427 3 Results

# 428 3.1 Surface-Water Extent

Median surface-water extent as well as the amount of water added and lost from the 429 surface between wet and dry periods was found to vary considerably across the study area 430 (Figure 4 and 5). Analysis of the median total surface-water extent between the PPR and the NP 431 demonstrated that the PPR had 2.6 times greater surface-water extent than the NP (Table 7). The 432 PPR also showed greater variability in total surface-water extent, adding 5.7 ha km<sup>-2</sup> during very 433 wet conditions and losing 2.8 ha km<sup>-2</sup> during very dry conditions, for a maximum net difference 434 of 8 ha km<sup>-2</sup>. This can be compared to the NP which gained 1.6 ha km<sup>-2</sup> during very wet 435 conditions and lost 0.8 ha km<sup>-2</sup> during very dry conditions, a net difference of 2.4 ha km<sup>-2</sup> (Table 436 7). DCW, or water that was discontinuous with the stream network, showed greater expansion 437 and contraction in extent in both the PPR and NP, relative to CCW which intersected the stream 438 439 network. Consequently, DCW increased as a percent of total surface water during wet periods and decreased as a percent of total surface water in dry periods. This suggests that across the 440 study area, surface water that was disconnected from the stream network disproportionately 441 442 served a surface water storage function during wet periods, reducing the amount of water





443 contributing to downstream flooding. Similarly, DCWs disproportionately experienced loss

444 during dry periods.

445

#### 446 3.2 Relationship between Surface-Water Extent and Water Availability

447 Including PET instead of using precipitation alone tended to increase the percentage of 448 HUC8s showing a statistically significant relationship between surface-water extent and water availability across the different accumulation periods that we tested, although this was not true 449 for all time periods. For instance, the percent change from precipitation to precipitation minus 450 PET ranged from -1.4 to 38% for DCW and -6.3 to 24.3% for CCW. For DCW there was a jump 451 in the percentage of HUC8s showing a significant relationship between six and nine months, but 452 the percentage of HUC8s stabilized after this time period out to 36 months. CCW showed a 453 similar but smaller jump in the percentage of HUC8s with a significant relationship between six 454 455 and nine months (Table 6). At nine months, all images, regardless of being collected in the 456 spring, summer or fall, would include winter precipitation. We observed substantial spatial variability in the statistical relationship between surface-water extent and water availability. 457 458 Using nine months as the accumulation period, we observed a strong spatial pattern in DCW. PPR HUC8s tended to show a greater SWCR, exhibited by a substantial increase in surface-459 water extent with increased water availability, while HUC8s across the NP tended to show a 460 461 smaller SWCR, exhibited by minor to no increases in surface-water extent with increased water availability (Figure 6 and 7). For CCW, the spatial pattern was less consistent within the PPR or 462 ecoregion boundaries. Instead, HUC8s with a greater SWCR tended to be HUC8s with large 463 464 lakes or floodplains (Figure 6 and 7).

465





## 466 **3.3 Landscape Variables Explaining Variability in Surface-Water Response**

467	For DCW SWCR, when independent variables were assessed individually using
468	Spearman's rank correlation, the SWCR was greater in locations with fewer streams ( $R = -0.64$ ,
469	p<0.05), lower slope gradient (R = -0.59, p<0.05), higher wetland density (R = 0.52, p<0.05) and
470	total wetland area (R = 0.51, p<0.05), deeper minimum depth to water table (R = 0.59, p<0.05)
471	and where a greater proportion of the total surface water was disconnected from the stream
472	network ( $R = 0.42$ , p<0.05) (Table 8). When the relative importance of the variables was tested
473	using random forest, variables found to be the most important included, wetland density, stream
474	density, annual minimum depth to water table and the slope gradient (Table 8). However, after
475	accounting for the spatial autocorrelation in the DCW SWCR and the significance of the
476	variables, the DCW SWCR increased in the final feasible generalized least-squares model
477	(adjusted $R^2 = 0.66$ , F-statistic = 73.6) with (1) greater wetland density, (2) deeper depth to
478	groundwater, and (3) less anthropogenic drainage (Table 9). The variable most consistent
479	identified across statistical approaches was wetland density.
480	For CCW SWCR, fewer independent variables showed a significant Spearman rank
481	correlation. The SWCR for stream-connected water increased in locations with a greater total
482	wetland area ( $R = 0.48$ , p<0.05) and less average precipitation ( $R = -0.33$ , p<0.05) (Table 8).
483	Using random forest, the total wetland area and proportion of total water from large features
484	were found to be the most important variables in explaining variation. The final feasible
485	generalized least-squares model (adjusted $R^2 = 0.54$ , F-statistic = 37.4) also found the
486	relationship between CCW and surface-water availability (i.e., SWCR) was stronger with greater
487	total wetland area, but also found that it decreased with greater wetland density (Table 9).
400	

488





# 489 **4. Discussion**

490	Surface-water extent, and in particular surface water within well-studied portions of the
491	PPR, has been previously shown to exhibit seasonal and interannual patterns (Poff et al., 1997;
492	Beeri and Phillips, 2007; Vanderhoof et al., 2016) that can, in turn, influence the cumulative
493	hydrologic response of a watershed (Golden et al. 2016; Evenson et al. 2016; Ali and Creed
494	2017). What has been less studied is how surface-water dynamics vary across diverse
495	landscapes. This is particularly relevant when we consider the need for communities and local
496	agencies to plan ahead for expected changes in the precipitation regime associated with climate
497	change (Dore, 2005; Johnson et al., 2005; Millett et al., 2009). Our results demonstrated that the
498	relationship between surface-water extent and water availability (SWCR) is a function of both
499	climate and landscape variables and that the density of depressional wetlands, in particular,
500	played a key explanatory role in the observed landscape response to increased climate inputs.
501	Given our findings, we expect that changes in net precipitation from climate change or other
502	climatic forcings will disproportionately affect surface-water extent across the PPR relative to
503	the adjacent NP, and that these effects will be more evident in disconnected wetland systems
504	(DCWs) than in wetlands connected to the river network (CCWs). Surface waters that are
505	disconnected from the stream network showed a larger change in extent in response to wetter
506	conditions in landscapes with higher wetland densities. That is to say that landscapes with a
507	larger number of depressional features were found to show a greater increase in surface-water
508	extent in response to a wetter climate, relative to landscapes with fewer depressional features. In
509	landscapes with more concentrated water, greater total wetland area, but lower wetland density,
510	surface waters connected to the stream network showed more substantial expansion with
511	increased water availability. This finding suggests that the presence of stream-connected lakes





512	within large flat basins may be an important factor influencing surface-water expansion.
513	Previous research found lakes within the PPR to be important features that commonly experience
514	extensive surface-water expansion, subsuming adjacent wetlands during wet periods
515	(Vanderhoof and Alexander, 2016). These findings suggest that if climate conditions within the
516	U.S. portion of the PPR continue to get wetter, as predicted (e.g., Millett et al. 2009), then both
517	small wetland depressions and larger features, such as lakes and floodplains, will both serve
518	critical roles in storing increased inputs of surface water, which could prevent downstream
519	flooding.
520	Our study area was intentionally selected to encompass a large area with a wide range of
521	landscape conditions in regards to wetland and stream density and capacity for infiltration.
522	Across the study area, variation in the values of many of the variables (e.g., stream density,
523	wetland density) can be attributed to landscape age or the time since the last glacial retreat, and
524	corresponding variability in drainage development across the region (Ahnert, 1996). The
525	Wisconsin glacier retreated from the PPR by 11,300 BP, meaning the drainage system is still
526	developing and surface water is being stored in glacially formed depressions (Winter and
527	Rosenberry, 1998; Stokes et al., 2007). In contrast, the landscape to the west and south of the
528	PPR, is much older (>20,000 BP) with a well-developed drainage network (Clayton and Moran,
529	1982).
530	In addition to extensive human-induced wetland loss across the region (Miller et al.,
531	2009; Van Meter et al., 2015), the drainage network across the region is also increasingly
532	modified with the expansion of ditch networks and tile drainage in association with agricultural
533	activities (McCauley et al., 2015). Ditches, pipes and field tiles on the glacial till can hasten the
534	speed with which water leaves a location and lower the water table through increased water





535	withdrawal (De Laney, 1995; Blann et al., 2009; McCauley et al., 2015). We found in the FGLS
536	model, the expansion of disconnected water was inversely related to the abundance of estimated
537	anthropogenic drainage. Because anthropogenic drainage increases the rate at which water leaves
538	a location, it results in the loss or reduction of landscape-scale functions of wetlands and other
539	natural water storage features in the PPR (McCauley et al. 2015), and shifts the hydrologic
540	behaviors of watersheds towards those more commonly seen in the NP.
541	Evapotranspiration is known to be a primary mechanism for water loss in the PPR
542	(Winter and Rosenberry, 1998). By explicitly incorporating this value into the SWCR, we could
543	better isolate the effects of landscape-based components such as surface storage, stream density,
544	and topography. One challenging component to characterize was the capacity for water to
545	infiltrate through soil horizons. Depth to bedrock SSURGO data was found to be too patchy (i.e.,
546	too much missing data) to be useful. A variable that instead was found to correlate significantly
547	with the expansion of disconnected water was annual minimum depth to groundwater. The PPR
548	tended to have a deeper minimum depth while the NP had a shallower minimum depth, on
549	average. A reduction in infiltration due to the low permeability of glacial till (Sloan, 1972;
550	Winter and Rosenberry, 1995), would reduce the potential for increased water table elevations.
551	Concomitantly, with less infiltration, pulses of snowmelt or precipitation in the PPR would
552	instead be transported as overland flow and fill wetlands with available storage.
553	We must also consider that we may be missing key landscape variables that could explain
554	variability in the spatial response of surface-water extent to climate inputs. For example, major
555	landscape characteristics required for stream-connected surface water to expand include (1)
556	large, stream-connected water bodies such as lakes and (2) hydrologically-connected floodplains.
557	The influence of large water bodies was considered by including total wetland area and the





558 portion of water from larger (>8 ha) features, however we did not explicitly consider the 559 presence/absence of active floodplains beyond including stream density as a variable. Floodplain 560 activity typically exhibits strong seasonal patterns; however, the goal of our analysis was to focus on patterns of surface-water extent that occurred on longer-time scales (i.e., interannual 561 variability). Because of this, we excluded two Landsat path/rows from the analysis that were 562 563 originally included because strong seasonal flooding outweighed interannual patterns in climate 564 as evidenced by a lack of a relationship between climate indices (e.g., Standardized Precipitation 565 Index (12 months) and Palmer Hydrologic Drought Index) and surface-water extent. These path/rows included p30r27 which straddles North Dakota and Minnesota and exhibits strong 566 567 seasonal flooding of the Red River and p28r32 in the southeastern corner of Nebraska, which exhibits strong seasonal flooding of the Missouri River. However, even with the exclusion of 568 these two path/rows, the importance of floodplains is still evident in Figure 6B where we 569 570 observed greater SWCR in areas with an abundance of lakes or floodplain systems. Because 571 complete floodplain maps across the study area are lacking, we were not able to explicitly identify the role of floodplains in the CCW models. 572 573 In addition to decision points regarding study area extent, other decision points may have influenced our findings. For example, the period of time for which the greatest number of 574 575 HUC8s showed a significant SWCR was used as the climate accumulation period. This logic was 576 meant to avoid, to the extent possible, a HUC8 showing a zero SWCR because surface water 577 responded at a time period different than the one selected. However, its usage meant that the study results are limited to interpreting the relationship of surface-water extent to same year 578 579 climate inputs (or the previous 9 months) and may be less applicable to understanding the 580 relationship of surface-water extent to shorter (seasonal) or longer (multi-year) time periods. In





581	addition, decisions regarding image inclusion may have also influenced the analysis. Although
582	the Landsat images used in the analysis were selected strategically to represent historically dry,
583	average, and wet conditions, because the Landsat images were processed individually we were
584	ultimately limited in the number of Landsat images we could process. As more remotely sensed
585	products become available, such as the U.S. Geological Survey's Dynamic Surface Water Extent
586	(DSWE) Product, which plans to utilize the entire Landsat archive (1984 to present) (Jones,
587	2015), we could utilize many more images and reduce the uncertainty in estimates of the SWCR
588	or watershed-specific response to available water. Although decision points regarding the data
589	included or excluded from the analysis are important to consider, this study provides an
590	improved understanding of how the relationship between surface-water extent and climate may
591	vary spatially across different landscapes.

592

### 593 5. Conclusion

Shifts in climate patterns and the frequency of extreme climate events will influence 594 surface-water extent. This has implications for habitat availability (Boschilia et al., 2008; 595 596 Calhoun et al., 2017), agricultural productivity (Mokrech et al., 2008; Gornall et al., 2010) and hydrologic connectivity (Golden et al. 2016; Ali and Creed 2017). This study demonstrated that 597 not only is surface-water extent variable across landscapes, but shifts in climate patterns will 598 599 have an uneven effect on surface-water extent across these different landscapes. The PPR 600 experienced a 2.6 fold greater surface-water extent than the adjacent NP under average 601 conditions and a 3.4 fold larger range in surface-water extent between drought and deluge 602 conditions. To move from ecoregion boundaries to a more functional characterization of the spatial distribution of surface water on the landscape, we used a statistical approach to explore 603





604	potentially significant landscape variables that could explain the spatially variable change in
605	surface water to climate inputs (precipitation minus evapotranspiration). Landscapes with higher
606	wetland density and less anthropogenic drainage showed a greater expansion of disconnected
607	(from the stream network) surface water (e.g., depressional wetlands) and wetter climatic
608	conditions relative to landscapes with fewer wetlands and more anthropogenic drainage.
609	Landscapes with fewer wetlands but more total surface water area (e.g., lakes, large river
610	systems) showed a greater expansion of stream-connected surface water and wetter climatic
611	conditions relative to landscapes with less total surface water area. Enhancing our knowledge of
612	spatial and temporal variability in the relationship between surface-water extent and climate
613	inputs can advance efforts to predict the hydrologic effects of climate change, including drought
614	and floods, on water resources and improve hydrological modeling in low gradient landscapes.
615	
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### 626 6. References





- Abatzoglou, J. T.: Development of gridded surface meteorological data for ecological applications and modelling, Int. J. Climatol., 33, 121-131, 2011.
- Acharya, G.: Approaches to valuing the hidden hydrological services of wetland ecosystems,
   Ecol. Econ., 35, 63-74, 2000.
- 631 Ahnert, F.: Introduction to Geomorphology, John Wiley & Sons, New York, 1996.
- Allen, C. R., Angeler, D. G., Cumming, G. S., Carl, F., and Twidwell, D.: Quantifying spatial
   resilience, J. Appl. Ecol., 53, 625-635, 2016.
- Ameli, A. A., Creed, I. F.: Quantifying hydrologic connectivity of wetlands to surface water
   systems, Hyrol. Earth Syst. Sci., 21, 1791-1808, 2017.
- Beeri, O. and Phillips, R. L.: Tracking palustrine water seasonal and annual variability in
  agricultural wetland landscapes using Landsat from 1997 to 2005, Glob. Change Biol., 13,
  897–912, 2007.
- Belsley, D. A.: Conditioning Diagnostics, Collinearity and Weak Data in Regression, John Wiley
  & Sons, New York, 1991.
- Belsley, D. A., Kuh, E., and Welsch, R.E.: Regression Diagnostics: Identifying Influential Data
  and Sources of Collinearity, John Wiley & Sons, New York, 1980.
- Betts, M. G., Ganio, L. M., Huso, M. M. P., Som, N. A., Huettmann, F., Bowman, J., and Wintle,
  B. A.: Comment on "Methods to account for spatial autocorrelation in the analysis of species distributional data: A review.", Ecography, 32, 374–378, 2009.
- Blann, K. L., Anderson, J. L., Sands, G. R., and Vondracek, B.: Effects of agricultural drainage
  on aquatic ecosystems: A review, Crit. Rev. Environ. Sci. Technol., 39, 909–1001,
  doi:10.1080/10643380801977966, 2009.
- Boschilia, S. M., Oliveira, E. F., and Thomaz, S. M.: Do aquatic macrophytes co-occur
  randomly? An analysis of null models in a tropical floodplain, Oecologia, 156, 203-214, 2008.
- Breusch, T. S. and Pagan, A. R.: A simple test for heteroskedasticity and random coefficient
  variation, Econometrica, 47, 1287–1294, JSTOR 1911963, MR 545960, 1979.
- Bryson, R. A. and Hare, F. K.: Climates of North America, in: World Survey of Climatology,
  Vol. 11, Lansberg, H. E., (Ed.), Elsevier, New York, 47 pp., 1974.
- Calhoun, A. J. K., Mushet, D. M., Bell, K. P., Boix, D., Fitsimons, J. A., and Isselin-Nondedeu,
  F.: Temporary wetlands: challenges and solutions to conserving a "disappearing" ecosystem,
  Biol. Conserv., 211, 3-11, 2017.
- Carroll, R. W., Pohll, G. M., Tracy, J., Winter, T., and Smith, R.: Simulation of a semipermanent
  wetland basin in the Cottonwood Lake Area, East-Central North Dakota, J. Hydrol. Eng., 1,
  70-84, 2005.
- Christensen, J. R., Nash, M. S., and Neale, A.: Identifying riparian buffer effects on stream
   nitrogen in southeastern coastal plain watersheds, Environ. Manage. 52, 1161–1176, 2013.
- Clayton, L. and Moran, S. R.: Chronology of late Wisconsinan glaciation in middle North
   America, Quaternary Sci. Rev., 1, 55–82, 1982.
- 666 Cohen, M. J., Creed, I. F., Alexander, L., Basu, N., Calhoun, A., Craft, C. B., D'Amico, E.,
- DeKeyser, S., Fowler, L., Golden, H., Jawitz, J. W., Kalla, P., Kirkman, L. K., Lane, C. R.,
  Lang, M., Leibowitz, S., Lewis, D. B., Marton, J. M., McLaughlin, D. L., Mushet, D.,
- Raanan-Kipperwas, H., Rains, M. C., Smith, L., and Walls, S.: Do geographically isolated
- 670 wetlands influence landscape functions?, P. Natl. Acad. Sci. U.S.A., 113, 1978-1986, doi:
- 671 10.1073/pnas.1512650113, 2016.





672	Cowardin, L. M., Carter, V., Golet, F. C., and LaRoe, E. T.: Classification of wetlands and
673	deepwater habitats of the United States, U.S. Fish and Wildlife Service, Washington, DC,
674	FWS/OBS-79/31, 1979.
675	Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., and
676	Pasteris, P. A.: Physiographically-sensitive mapping of temperature and precipitation across
677	the conterminous United States, Int. J. Climatol., 28, 2031-2064, doi: 10.1002/joc.1688,
678	2008.
679	De Laney, T. A.: Benefits to downstream flood attenuation and water quality as a result of
680	constructed wetlands in agricultural landscapes, J. Soil Water Conserv., 50, 620-626, 1995.
681	Dore, M. H. I.: Climate change and changes in global precipitation patterns: What do we know?,
682	Environ. Int., 31, 1167-1181, 2005.
683	Dormann, C. F., McPherson, J. M., Araujo, M. B., Bivand, R., Bolliger, J., Carl, G., Davies, R.
684	G., Hirzel, A., Jetz, W., Kissling, W. D., Kühn, I., Ohlemüller, R., Peres-Neto, P. R.,
685	Reineking, B., Schröder, B., Schurr, F. M., and Wilson, R.: Methods to account for spatial
686	autocorrelation in the analysis of species distributional data: A review, Ecography, 30, 609-
687	628, 2007.
688	Dunn, O. J.: Multiple comparison among means, J. Am. Stat. Assoc., 56, 52–64, 1961.
689	Eamus, D., Hatton, T., Cook, P., and Colvin, C.: Ecohydrology: vegetation function, water and
690	resource management, CSIRO Publishing, Australia, 360 pp., 2006.
691	Euliss Jr., N. H. and Mushet, D. M.: Water-level fluctuation in wetlands as a function of
692	landscape condition in the Prairie Pothole Region, Wetlands, 16, 587–59, 1996.
693	Evenson, G. R., Golden, H. E., Lane, C. R., D'Amico, E.: An improved representation of
694	geographically isolated wetlands in a watershed-scale hydrologic model, Hydrol Processes,
695	doi:10.1002/hyp.10930, 2016.
696	
697	Fausey, N. R., Doering, E. J., and Palmer, M. L.: Purposes and benefits of drainage, in: Farm
698 600	drainage in the United States: History, status, and prospects, Pavelis, G. A. (Ed.), USDA
699	Economic Research Service, Washington, DC, Misc. Publ. 1455, 4 pp., 1987.
700	Feddema, J. J.: A revised Thornthwaite-type global climate classification, Phys. Geogr., 26, 442-
701 702	466, 2005. Fleiss, J. L.: Statistical methods for rates and proportions (2 <sup>nd</sup> ed.), John Wiley & Sons, New
702	York City, NY, 1981.
703	Flint, R. F.: Glacial and Quaternary Geology, John Wiley & Sons, New York City, NY, 1971.
705	Forbes, A. D.: Classification-algorithm evaluation: Five performance measures based on
706	confusion matrices. J. Clinical Monitoring, 11(3), 189-206, 1995.
707	Gleason, R. A. and Tangen, B. A.: Ecosystem services derived from wetland conservation
708	practices in the United States prairie pothole region with an emphasis on the U.S., in:
709	Department of Agriculture Conservation Reserve and Wetlands Reserve Programs
710	Professional Paper 1745: Floodwater storage, Gleason, R. A., Laubhan, M. K., Euliss Jr., M.
711	K. (Eds.), U.S. Geological Survey, Reston, VA, 7 pp., 2008.
712	Golden, H. E., Sander, H. A., Lane, C. R., Zhao, C., Price, K., D'Amico, E., Christensen, J.R.:
713	Relative effects of geographically isolated wetlands on streamflow: A watershed-scale
714	analysis, Ecohydrology, 9(1), 21-38, 2016.
715	Golden, H. E., Creed, I. F., Ali, G., Basu, N. B., Neff, B. P., Rains, M. C., McLaughlin, D. L.,
716	Alexander, L. C., Ameli, A. A., Christensen, J. R., Evenson, G. R., Jones, C. N., Lane, C. R.,





- and Lang, M.: Integrating geographically isolated wetlands into land management decisions,
   Front. Ecol. Environ., 15, 319-327, 2017.
- Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., and Wiltshire, A.: Implications
  of climate change for agricultural productivity in the early twenty-first century, Philos. Trans.
  R. Soc. B. Biol. Sci., 365, 2973–2989, 2010.
- Green, A. A., Berman, M., Switzer, P., and Craig, M. D.: A transformation for ordering
   multispectral data in terms of image quality with implications for noise removal, IEEE T.
- 724 Geosci. Remote, 26, 65–74, 1988.
- Hamilton, S. K., Sippel, S. J., and Melack, J. M.: Comparison of inundation patterns among
  major South American floodplains, J. Geophys. Res., 107, 1-14, 2002.
- Hamilton, S. K., Sippel, S. J., and Melack, J. M.: Seasonal inundation patterns in two large
  savanna floodplains of South America: the Llanos de Moxos (Bolivia) and the Llanos del
  Orinoco (Venezuela and Colombia), Hydrol. Process, 18, 2103–2116, 2004.
- Hamon, W. R.: Estimating potential evapotranspiration, J. Hydr. Eng. Div. ASCE, 87, 107-120,
  1961.
- Hanushek, E. A.: Efficient estimators for regressing regression coefficients, Am. Stat., 28, 66–
  67, 1974.
- Heiler, G., Hein, T., Schiemer, F., and Bornette, G.: Hydrological connectivity and flood pulses
  as the central aspects for the integrity of a river-floodplain system, Regul. River, 11, 351–
  361, 1995.
- Heine, R. A., Lant, C. L., Sengupta, R. R.: Development and comparison of approaches for
  automated mapping of stream channel networks. Annals of the Assoc of Am Geographers,
  94(3), 477–490, 2004.
- Hendrickx, J.: Perturb: Tools for evaluating collinearity, R package version 2.05,
   <a href="http://CRAN.R-project.org/package=perturb">http://CRAN.R-project.org/package=perturb</a>, 2012.
- Hoffmann, C. C., Kjaergaard, C., Uusi-Kämppä, J., Hansen, H. C., and Kronvang, B.:
  Phosphorus retention in riparian buffers: Review of their efficiency, J. Environ. Qual., 38, 1942-1955, 2009.
- Homer, C., Dewitx, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.,
  Wickham, J., and Megown, K.: Completion of the 2011 National Land Cover Database for
  the conterminous United States representing a decade of land cover change information,
- 748 Photogramm. Eng. Rem. S., 81, 345–354, 2015.
- Huang, S., Dahal, D., Young, C., Chander, G., and Liu, S.: Integration of Palmer Drought
  Severity Index and remote sensing data to simulate wetland water surface from 1910 to 2009
  in Cottonwood Lake area, North Dakota, Remote Sens. Environ., 115, 3377-3389, 2011.
- Johnson, W. C., Millett, B. V., Gilmanov, T., Voldseth, R. A., Guntenspergen, G. R., and
  Naugle, D. E.: Vulnerability of northern prairie wetlands to climate change, Bioscience, 55,
  863–872, 2005.
- Jones, J. W.: Efficient wetland surface water detection and monitoring via Landsat: comparison
  with in situ data from the Everglades depth estimation network, Remote Sens., 7, 1250312538, 2015.
- Kahara, S. N., Mockler, R. M., Higgins, K. F., Chipps, S. R., and Johnson, R. R.: Spatiotemporal
  patterns of wetland occurrence in the Prairie Pothole Region of eastern South Dakota,
- 760 Wetlands, 29, 678-689, 2009.





- Kantrud, H. A., Krapu, G. L., and Swanson, G. A.: Prairie basin wetlands of the Dakotas: a
  community profile, U.S. Fish and Wildlife Service Biological Report 85(7.28), Washington,
  DC, 1989.
- King, K. W., Fausey, N. R., and Williams, M. R.: Effect of subsurface drainage on streamflow in
   an agricultural headwater watershed, J. Hydrol., 519, 438–445, 2014.
- Kuppel, S., Houspanossian, J., Nosetto, M. D., and Jobbágy, E. G.: What does it take to flood the
  Pampas? Lessons from a decade of strong hydrological fluctuations, Water Resour. Res., 51,
  2937-2950, doi:10.1002/2015WR016966, 2015.
- LaBaugh, J. W., Winter, T. C., and Rosenberry, D. O.: Hydrologic functions of prairie wetlands,
   Great Plains Res., 4, 17-37, 1998.
- Lewis, J. B. and Linzer, D. A.: Estimating regression models in which the dependent variable is
  based on estimates, Polit. Anal., 13, 345-364, 2005.
- Liaw, A. and Wiener, M.: Breiman and Cutler's random forests for classification and regression,
   R package version 4.6-12, R Foundation for Statistical Computing, Vienna, Austria,
   https://www.stat.berkeley.edu/~breiman/RandomForests/, 2005.
- Masek, J. G., Vermote, E. F., Saleous, N., Wolfe, R., Hall, E. F., Huemmrich, F., Gao, F., Kutler,
  J., and Teng-Kui, L.: A Landsat surface reflectance data set for North America, 1990–2000,
  IEEE Geosci. Remote S., 3, 68–72, 2006.
- McCauley, L. A., Anteau, M. J., Van Der Burg, M. P., and Wiltermuth, M. T.: Land use and
  wetland drainage affect water levels and dynamics of remaining wetlands, Ecosphere, 6, 1–
  20, 2015.
- Millett, B., Johnson, W. C., and Guntenspergen, G.: Climate trends of the North American
  Prairie Pothole Region 1906-2000, Climatic Change, 93, 243-267, 2009.
- Mitchell, K. E., Lohmann, D., Houser, P. R., Wood, E. F., Schaake, J. C., Robock, A., Cosgrove,
  B. A., Sheffield, J., Duan, Q., Luo, L., Higgins, R. W., Pinker, R. T., Tarpley, J. D.,
- 786 Lettenmaier, D. P., Marshall, C. H., Entin, J. K., Pan, M., Shi, W., Koren, V., Meng, J.,
- Ramsay, B. H., and Bailey, A. A.: The multi-institution North American Land Data
- Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a
- continental distributed hydrological modeling system, J. Geophy. Res., 109, D07S90,
- 790 doi:10.1029/2003JD003823, 2004.
- Mokrech, M., Nicholls, R. J., Richards, J. A., Henriques, C., Holman, I. P., and Shackley, S.:
- Regional impact assessment of flooding under future climate and socio-economic scenarios
  for East Anglia and North West England, Climatic Change, 90, 31-55, 2008.
- Murphy, M. A., Evans, J. S., and Storfer, A.: Quantifying *Bufo boreas* connectivity in Yellowstone
   National Park with landscape genetics, Ecology, 91, 252–261, 2010.
- Niemuth, N. D., Wangler, B., and Reynolds, R. E.: Spatial and temporal variation in wet area of
  wetlands in the prairie pothole region of North Dakota and South Dakota, Wetlands, 30,
  1053-1064, 2010.
- 799 NOAA National Climatic Data Center: Data Tools: 1981-2010 Normals,
- 800 <u>http://www.ncdc.noaa.gov/cdo-web/datatools/normals</u>, last access: 12, January, 2017, 2014.
- Poff, N. L., Allan, J. D., Bain, M. B., Karr, J. R., Prestegaard, K. L., Richter, B. D., Sparks, R.
  E., and Stromberg, J. C.: The natural flow regime, BioScience, 47, 769-784, 1997.
- Pringle, C. M.: Hydrologic connectivity and the management of biological reserves: a global
  perspective, Ecol. Appl., 11, 981–998, 2001.





805	Rosenberry, D. O., Stannard, D. I., Winter, T. C., and Martinez, M. L.: Comparison of 13
806	equations for determining evapotranspiration from a prairie wetland, Cottonwood Lake area,
807	North Dakota, USA, Wetlands, 24, 483–497, 2004.
808	Sass, G. Z. and Creed, I. F.: Characterizing hydrodynamics on boreal landscapes using archived
809	synthetic aperture radar imagery, Hydrol. Process., 22, 1687-1699, 2008.
810	Sayler, K. L., Acevedo, W., Soulard, C. E., and Taylor, J. L.: Land cover trends dataset, 2000-
811	2011, U.S. Geological Survey, http://dx.doi.org/10.5066/F7DJ5CNT, 2015.
812	Schmidt, F., Persson, A.: Comparison of DEM data capture and topographic wetness indices,
813	Precision Agriculture, 4(2), 179-192, 2003.
814	Shaw, D. A., Vanderkamp, G., Conly, F. M., Pietroniro, A., and Martz, L.: The fill-spill
815	hydrology of prairie wetland complexes during drought and deluge, Hydrol. Process., 26,
816	3147-3156, 2012.
817	Skaggs, R. W., Breve, M. A., and Gilliam, J. W.: Hydrologic and water quality impacts of
818	agricultural drainage, Crit. Rev. Environ. Sci. Technol., 24, 1–32,
819	doi:10.1080/10643389409388459, 1994.
820	Sloan, C. E.: Ground-water hydrology of Prairie Potholes in North Dakota, U.S. Geological
821	Survey Professional Paper, 585, 1-27, 1972.
822	Smith, L. C., Sheng, Y., and MacDonald, G. M.: A first pan-arctic assessment of the influence of
823	glaciation, permafrost, topography and peatlands on northern hemisphere lake distribution, Permafrost Periglac., 18, 201-208, 2007.
824 825	Stokes, C. R., Popovnin, V., Aleynikov, A., Gurney, S. D., and Shahgedanova, M.: Recent
825 826	glacier retreat in the Caucasus Mountains, Russia, and associated increase in supraglacial
827	debris cover and supra-/proglacial lake development, Ann. Glaciol., 46, 195-203, 2007.
828	Turin, G.: An introduction to matched filters, IRE T. Inform. Theor., 6, 311–329, 1960.
829	U.S. Department of Agriculture, National Resources Conservation Service: Watershed Boundary
830	Dataset,
831	http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/water/watersheds/dataset/?cid=nrcs
832	143_021625, last access: 20 September 2016, 2015.
833	U.S. Department of Agriculture, Natural Resources Conservation Service: Soil Survey
834	Geographic (SSURGO) Database, https://sdmdataaccess.sc.egov.usda.gov, last access: 25
835	May 2017, 2017.
836	U.S. Fish and Wildlife Service: National Wetlands Inventory, http://www.fws.gov/wetlands/, last
837	access: 1 September 2016, 2010.
838	U.S. Geological Survey: The National Hydrography Dataset (NHD) concepts and content,
839	available at: http://nhd.usgs.gov/chapter1/ chp1_data_users_guide.pdf, 2010.
840	U.S. Geological Survey: The National Hydrography Dataset (NHD),
841	ftp://nhdftp.usgs.gov/DataSets/Staged/States/FileGDB/ HighResolution, last access: 2
842	September 2017, 2013.
843	van der Kamp, G. W., Stolte, J., and Clark, R. G.: Drying out of small prairie wetlands after
844	conversion of their catchments from cultivation to permanent brome grass, Hydrolog. Sci. J.,
845	44, 387–397, 1999.
846	Van Meter, K. J. and Basu, N. B.: Signatures of human impact: size distributions and spatial
847	organization of wetlands in the Prairie Pothole landscape, Ecol. Appl., 25, 451–465, 2015.
848	Vanderhoof, M. K., Alexander, L. C., and Todd, M. J.: Temporal and spatial patterns of wetland
849	extent influence variability of surface water connectivity in the Prairie Pothole Region,
850	United States, Landscape Ecol., 31, 805–824, 2016.





- Vanderhoof, M. K. and Alexander, L. C.: The role of lake expansion in altering the wetland
  landscape of the Prairie Pothole Region, Wetlands, 36, 309-321, 2016.
- Vanderhoof, M. K., Christensen, J. R., and Alexander, L. C.: Patterns and drivers for wetland
  connections in the Prairie Pothole Region, United States, Wetl. Ecol. Manag., 25, 275-297,
  2017.
- Venables, W. N. and Ripley, B. D.: Modern Applied Statistics with S, Fourth Edition, Springer,
  New York, 2002.
- Villalobos-Jimenez, G. and Hassall, C.: Effects of the urban heat island on the phenology of
  Odonata in London, UK, Int. J. Biometeorol., 61, 1337-1346, 2017.
- Wagener, T., Sivapalan, M., Troch, P., and Woods, R.: Catchment classification and hydrologic
   similarity, Geogr. Compass, 1, 901-931, 2007.
- Wiche, G. G.: Lake levels, streamflow, and surface-water quality in the Devil's Lake Area, North
  Dakota, U.S. Geological Survey Fact Sheet, Bismarck, ND, 8 pp., 1996.
- Willmott, C. J. and Feddema, J. J.: A more rational climatic moisture index, Prof. Geogr., 44, 8488, 1992.
- Winter, T. C.: The concept of hydrologic landscapes, J. Am. Water Res. Assoc., 37, 335-349,
  2001.
- Winter, T. C. and Rosenberry, D. O.: The interaction of ground water with Prairie Pothole
  wetlands in the Cottonwood Lake area, east-central North Dakota, 1979–1990, Wetlands, 15,
  193–211, 1995.
- Winter, T. C. and Rosenberry, D. O.: Hydrology of prairie pothole wetlands during drought and
   deluge: 7-year study of the Cottonwood Lake wetland complex in North Dakota in the
- perspective of longer term measured and proxy hydrological records, Climatic Change, 40,
  189-209, 1998.
- 875 Yao, T., Pu, J., Lu, A., Wang, Y., and Yu, W.: Recent glacial retreat and its impact on
- hydrological processes on the Tibetan Plateau, China, and surrounding regions, Arct. Antarct.
  Alp. Res., 39, 642-650, 2007.
- Zhang, B., Schwartz, F. W., and Liu, G.: Systematics in the size structure of prairie pothole lakes
  through drought and deluge, Water Resour. Res., 45, W04421, 2009.
- Zhu, Z. and Woodcock, C. E.: Automated cloud, cloud shadow, and snow detection in
   multitemporal Landsat data: An algorithm designed specifically for monitoring land cover
   abar as Barnata Sana Environ 152, 217, 224, 2014
- change, Remote Sens. Environ., 152, 217-234, 2014.
- 883
- 884
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<b>Table 1.</b> A summary of the Landsat images utilized within each selected path/row. Landsat TM images were used for dates 2011 and earlier. Landsat 8 OLI images were used for 2013 forward. DOY: day of year; PHDI: Palmer Hydrological Drought Index. *p37r26 was considered NP because of its dissimilarity with the rest of the PPR.	Min. Max. Mean PHDI PHDI PHDI (%) (%) (%)	4 99 45	2 99 51	4 99 54	7 100 69	2 100 45	5 94 38	3 100 67	7 99 45	1 99 49	2 96 38	1 99 52
lected path/rc day of year; F PPR.	Year Range	1987-2010	1988-2010	1988-2008	1990-2011	1988-2013	1986-2011	1990-2011	1989-2011	1988-2015	1985-2013	1987-2013
in each se d. DOY: d est of the	Fall (DOY 244-335)	2	4	7	9	б	4	7	2	5	7	5
lized with )13 forwar with the r	Summer (DOY 152-243)	4	33	4	7	5	5	9	5	2	7	9
mages uti ised for 20 similarity	Spring (DOY 60-151)	9	10	ю	6	5	9	2	9	8	Γ	4
e Landsat ges were u e of its dis	Number of Images	12	17	6	17	13	15	15	13	15	16	15
<b>Table 1.</b> A summary of the Landsat images utilized within each selecte earlier. Landsat 8 OLI images were used for 2013 forward. DOY: day o was considered NP because of its dissimilarity with the rest of the PPR	PPR/Northern Path/Row Prairie (NP) (primary)	NP	NP	PPR	PPR	PPR	NP	PPR	PPR	NP	NP	NP*
<b>Table 1.</b> A : earlier. Lane was conside	Path/Row	p26r30	p26r32	p27r30	p29r29	p30r30	p30r31	p31r27	p31r29	p33r28	p36r28	p37r26

 $\frac{4}{2}$ 

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Total

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Landsat Path/Row	Landsat date	NAIP date(s)		Gap (days)	IQHA	SP12	Number of points	OE (%)	CE (%)	0A (%)	DC (%)	RB (%)	
p26r32	28-Jun-04	23-Jun-04 and 07-Jul-04	-04	-5 to $+9$ days	0.57	0.14	947 707	6.3 11 o	5.9 0.2	97.4 07.5	93.9 00 5	-0.5	
p29r29	14-Jul-15 13-Oct-06	25-Sep-06	CT-	-4 10 -2 uays -18 days	-0.34 2.3	-0.08	814	11.1	2.5	93.6	93.0	 -8.8	
p29r29	8-Oct-10	17-Sep-10 and 20-Sep-10		+18  to  +21  days	9.63	3.06	959	1.9	3.3	97.4	96.4	1.4	
p31r29	17-Jul-04	10-Jul-04 and 14-Jul-04		-7 to -3 days	-0.4	-0.04	1302	7.4	1.5	97.2	95.4	-6.0	
p33r28	13-Jul-03	11-Jul-03 and 15-Jul-03		-2 to +2 days	-2.74	-0.91	908	10.6	27.0	85.5	80.4	22.5	
p37r26	31-Jul-11	16-Jul-11 and 19-Jul-11		-15 to -12 days	2.96	1.29	498	16.8	9.7	90.2	86.6	-7.9	
		NAIP - Inundated I	NAIP - Non- Inundated	Total d									
Landsat - Inundated	nundated	2052	183	2235									
Landsat - N Total	Landsat - Non-Inundated Total	190 2242	3710 3893	3900 6135									
Omission e Commissio	Omission error for water (%) Commission error for water (%)												
Overall Accuracy (%) Dice Coefficient Relative Bias	curacy (%) icient as	93.9 91.7 0.0											

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Table 4. Independent variables considered in the landscape analysis and the distribution of values for each variable across the 8-digit hydrological units (HUC8s). Mean values for the HUC8s within the Prairie Pothole Region (PPR) and Northern Prairie (NP) are also

901 902 903 904 905





Independent Variables	Units	Range	25th %	50th %	75th %	PPR (avg)	NP (avg)	Source
Wetland and Stream Characteristics								
Stream density	m ha <sup>-1</sup>	0.1 to 26.1	7.2	11.4	15.0	$7.8^{\rm a}$	$14.5^{b}$	High-Resolution NHD (USGS 2013)
Total wetland density	no ha <sup>-1</sup>	0 to 0.2	0.02	0.03	0.06	$0.06^{a}$	$0.03^{b}$	NWI (USFWS 2010)
Total wetland areal abundance	ha ha <sup>-1</sup>	0 to 0.7	0.02	0.03	0.08	$0.08^{a}$	$0.05^{b}$	NWI (USFWS 2010)
Portion of total water area from large features	%	0.1 to 97.8	32.1	44.7	58.0	$45.0^{a}$	$47.2^{a}$	NWI (USFWS 2010, Zhang et al., 2009)
Portion DCW of total surface water	%	0 to 100	10.6	24.4	50.0	44.5 <sup>a</sup>	$22.8^{\mathrm{b}}$	Landsat and NHD (USGS 2013)
Climate Averages								
Moisture Index Average	٢	-0.4 to 0.7	-0.1	-0.04	0.2	$0.04^{a}$	-0.03ª	PRISM (Daly et al., 2008)
Precipitation Average	mm yr-1	312.3 to 1007.8	490.3	599.6	790.8	641.5 <sup>a</sup>	624.3 <sup>a</sup>	PRISM (Daly et al., 2008)
PET Average	mm yr-1	496.2 to 683.0	564.2	595.5	628.9	595.5 <sup>a</sup>	594.8 <sup>a</sup>	PRISM (Daly et al., 2008)
Soil and Topography								
Available water storage (0-150 cm), weighted	cm	7.6 to 29.5	18.0	22.8	24.7	$24.0^{a}$	$19.1^{\rm b}$	SSURGO (Soil Survey Staff, 2017)
Annual minimum depth to water table	cm	0.1 to 69.0	11	24.8	43.3	$40.5^{a}$	$17.9^{b}$	SSURGO (Soil Survey Staff, 2017)
Ksat	μm sec <sup>-1</sup>	2.1 to 107.7	8.4	13.8	22.5	21.4 <sup>a</sup>	$21.2^{a}$	SSURGO (Soil Survey Staff, 2017)
Slope gradient, weighted average Human Influence	%	1.5 to 19.2	3.0	4.3	7.1	3.3 <sup>a</sup>	7.1 <sup>b</sup>	SSURGO (Soil Survey Staff, 2017)
Agricultural land cover	%	0.1 to 92.0	25.2	62.8	80.5	72.6 <sup>a</sup>	$39.6^{\mathrm{b}}$	2011 NLCD (Homer et al., 2015)
Percent drained by anthropogenic means	%	0 to 93.0	5.9	50.1	77.8	$61.7^{a}$	$32.5^{\mathrm{b}}$	2011 NLCD and SSURGO

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**Percent** drained -0.16 0.51\*-0.07 -0.32\* 0.63\*0.64\*0.50\*0.57\*0.22 -0.07 0.25 -0.01 0.26 -0.2 0.23 Ag land cover -0.63\* 0.33\*-0.33\* -0.03 0.80\*-0.08  $0.66^{*}$ 0.46\*0.11 -0.24 0.66\* 0.69\*0.02 0.05 applied to the p-values and significant correlations (p<0.05) are starred. DCW: surface water disconnected from the stream network, CCW: continuously connected surface water, MI: Moisture Index, PET: potential evapotranspiration, precip: precipitation, lg: large, Slope gradient -0.16 -0.19 -0.58\* -0.34\* -0.41\*-0.61\*-0.44\*  $0.66^{*}$ -0.17 -0.25 -0.29 0.12 0.1 Ksat -0.47\* 0.11 -0.03 0.03 -0.05 0.19 -0.01 0.08 0.14 -0.2 0.21 0.01 Annual min depth to water  $0.54^{*}$ -0.62\*  $0.54^{*}$ table -0.04 0.67\*0.44\*0.49\*0.29 0.26 -0.1 -0.21 storage (0-Avail water 150 cm) -0.34\* 0.37\*0.60\*0.48\*-0.07 0.29 0.26 0.05 -0.11 0.21 \_ PET 0.03 0.15 -0.05 0.09 -0.2 0.25 -0.1 -0.1 0 \_ Precip -0.05 -0.26 0.19 -0.16  $0.86^{*}$ 0.20-0.21 0.06 --0.34\* -0.29 0.33\*-0.22 0.18 ¥ 0.03 0.24 \_ Dominance of lg. water bodies ag: agricultural, Ksat: saturated hydraulic conductivity, na: not applicable -0.63\* -0.05 -0.02 -0.04 0.18 0.44 Wetland areal abund. 0.48\*-0.09 -0.37\* 0.79\*0.27 -Wetland density -0.33\* 0.48\*0.15 0.32\*Stream density -0.66\* -0.16 -0.38\* connected Portion 0.45\*dis--0.11 covariate CCW autona \_ covariate DCW auto-Dominance of lg Agricultural land Portion DCW of Wetland density Stream density autocovariate CCW storage (0-150 Slope gradient depth to water autocovariate Wetland areal Variable water bodies Precipitation Annual min Avail water abundance total water DCW Ksat cover table PET cm) W

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Table 5. Spearman rank correlation values between the independent variables considered in the analysis. Bonferonni correction was

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Accumulated Period	Precip DCW (%)	P - PET DCW (%)	Inclusion of PET change (DCW)	Precip CCW (%)	P - PET CCW (%)	Inclusion of PET change (CCW)
3 months	19.4	27.1	7.6	15.3	28.5	13.2
6 months	5.6	31.9	26.4	9.0	33.3	24.3
9 months	20.8	59.7	38.9	27.1	48.6	21.5
12 months	45.8	50.7	4.9	42.4	41.0	-1.4
18 months	24.3	58.3	34.0	25.7	39.6	13.9
24 months	52.1	50.7	-1.4	43.8	37.5	-6.3
30 months	28.5	55.6	27.1	27.1	43.1	16.0
36 months	54.9	54.9	0.0	47.2	44.4	-2.8
HUC8s with a sig relationship in at least 1	65.3	75.7	10.4	59.0	67.4	8.3

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**Table 6.** The percent of HUC8s across the study area that showed a significant relationship (p<0.05) between surface-water extent and

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Region	Path/ rows (all or part)	Total area (km²)	Min (ha km <sup>-2</sup> )	Max (ha km <sup>-2</sup> )	Median (ha km <sup>-2</sup> )	Added min to max (ha km <sup>-2</sup> )	Reduction from median to min (%)	Increase from median to max (%)	Min (% of all) (area)	Max (% of all) (area)	Median (% of all) (area)
PPR TSW	7	146,309	3.51	11.99	6.33	8.48	44.6	89.2	٢	٢	٢
NP TSW	6	173,026	1.62	4.07	2.45	2.45	33.9	66.1	٢	ł	٢
PR CCW	7	146,309	2.82	7.56	4.44	4.74	36.5	70.4	80.3	63.1	70.1
VP CCW	6	173,026	1.44	3.11	2.06	1.66	30.0	50.5	89.1	76.3	84.2
PPR DCW	7	146,309	0.69	4.42	1.90	3.73	63.4	133.4	19.7	36.9	29.9
NP DCW	6	173 026	0.18	0 97	0 30	0.79	54 4	149.7	10.9	737	15.8

Table 7. Surface-water extent conditions summarized for the Prairie Pothole Region (PPR) and adjacent Northern Prairie (NP). TSW:

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evapotranspiration, Ksat: saturated hydraulic conductivity, DCW: disconnected surface water, CCW: continuously, connected surface importance as determined by random forest models are also presented for each variable (i.e., increase in node purity). PET: potential Table 8. Spearman rank correlation values between the dependent variables and each of the independent variables considered in the analysis. Bonferonni correction was applied to the p-values and significant correlations (p<0.05) are starred. Relative variable

		(annually ( ) and and and	NC) actinded	Response (UUW, 9 monuls)
Variable	Spearman rank correlation	Increase in node purity	Spearman rank correlation	Increase in node purity
Autocovariate	0.79*	0.081	0.53*	0.108
Portion DCW is of total surface water	0.42*	0.012	-0.11	$0.334^{1}$
Stream density	-0.64*	$0.036^{1}$	-0.15	0.060
Wetland density	0.52*	$0.048^{1}$	0.27	$0.057^{1}$
Wetland areal abundance	0.51*	$0.017^{1}$	0.48*	$0.855^{1}$
Portion of total water from large features	-0.01	0.004	0.30	$0.556^{1}$
Moisture Index (average)	-0.03	0.005	-0.28	$0.053^{1}$
Precipitation (average)	-0.10	$0.008^{1}$	-0.33*	$0.039^{1}$
PET (average)	-0.06	$0.011^{1}$	-0.13	0.034
Available water storage (0-150 cm)	0.27	0.007	-0.01	0.061
Annual minimum depth to water table	$0.56^{*}$	$0.027^{1}$	0.09	0.046
Ksat	0.04	0.004	-0.08	$0.070^{1}$
Slope gradient, weighted average	-0.59*	$0.025^{1}$	-0.22	0.072
Agricultural land cover	0.31	0.005	-0.05	0.035
Percent drained by anthropogenic means	0.22	0.004	-0.04	0.020

included. 929

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to water availability	Variables	Coefficients	SE	t-value
D.F. = 145	Intercept	0.17	0.01	12.84
F-statistic = 73.6	Autocovariate	0.03	0.004	6.32
adjusted $\mathbf{R}^2 = 0.66$	Wetland density	0.90	0.23	3.96
	Minimum depth to groundwater	0.0021	0.0006	3.29
	Percent anthropogenically drained	-0.0004	0.0003	-1.25
Response of CCW water to water availability	Variables	Coefficients	SE	t-value
D.F. = 144	Intercept	0.018	0.01	1.43
F-statistic = 69.4	Wetland areal abundance	0.96	0.07	14.42
adjusted $R^2 = 0.58$	Wetland density	-0.43	0.21	-2.09
	Autocovariate	-0.12	0.01	-0.89

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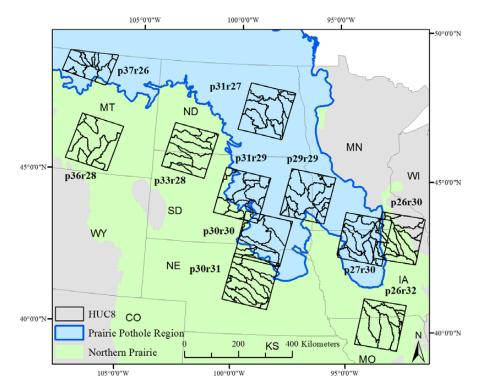
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Table 9. Feasible generalized least square models with residual weights applied relating the response (of surface-water extent to water

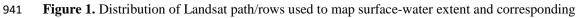




## 939 Figures



940



8-digit Hydrological Units (HUC8s) used for further analysis in relation to the boundary of the

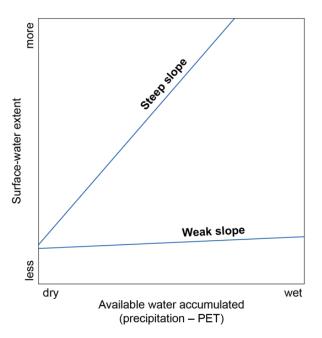
943 Prairie Pothole Region (PPR). The p37r26 behaved dissimilarly from the PPR and similarly to

944 the adjacent Northern Prairie (NP) in all regards and was therefore included with the NP for

analyses organized by PPR and NP.







947

948 Figure 2. Theoretical figure showing the derived dependent variable, or the Surface Water

949 Climate Response (SWCR), defined as the slope of the statistical relationship between

950 accumulated water and surface-water extent. Some areas show a greater SWCR or substantial

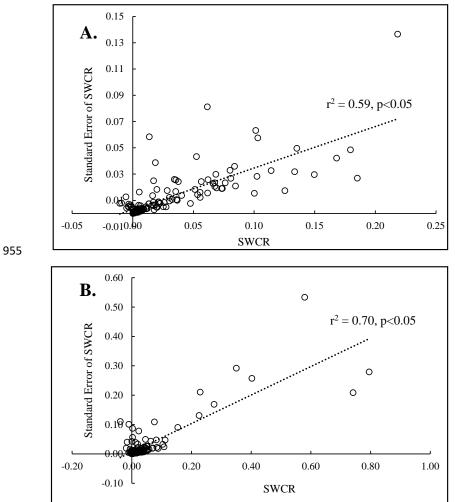
951 increase in surface-water extent as more water becomes available via precipitation minus

952 potential evapotranspiration (PET), while other areas show little to no change in surface-water

953 extent, presumably as excess water leaves the system through runoff or infiltration.







956

957 Figure 3. Standard errors of the Surface Water Climate Response (SWCR) tended to be

958 positively correlated with both A) discontinuous surface water (DCW) or surface water

disconnected from the stream network and B) continuously connected water (CCW) or surface

960 water connected to the stream network.





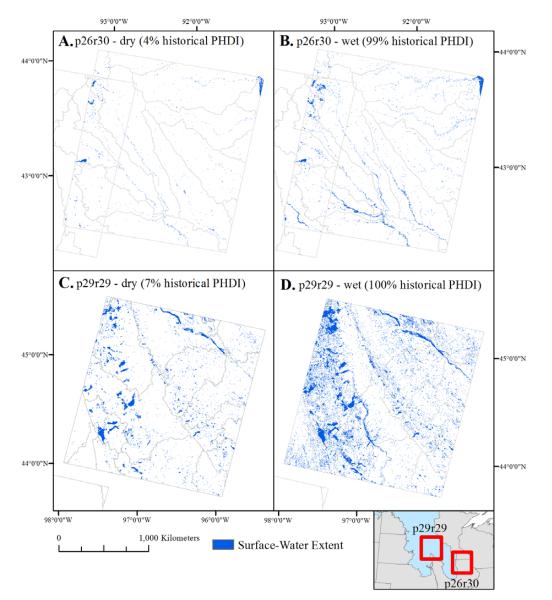
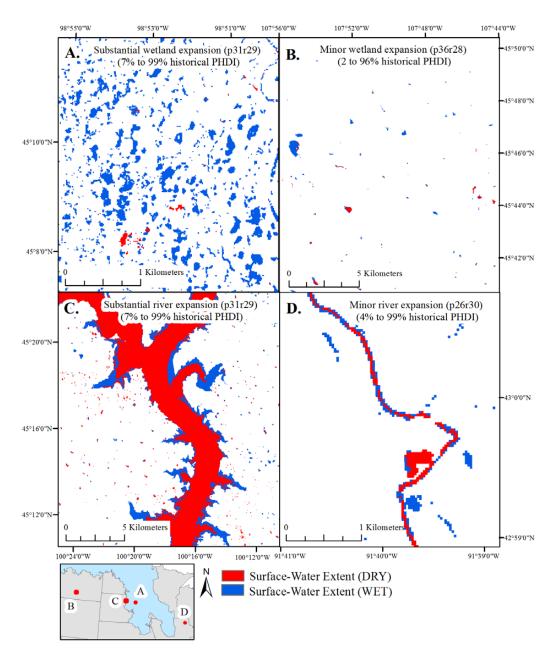


Figure 4. Mean surface-water abundance and the amount of "wetting up" varied substantially
between different Landsat path/rows. Portions of the Northern Prairie (e.g., p26r30) showed
relatively less surface-water extent and expansion (A and B) while portions of the Prairie Pothole
Region (e.g., p29r29) showed relatively more surface-water extent and expansion (C and D).
Note: not all water is visible at this zoomed-out scale. PHDI: Palmer Hydrological Drought
Index







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971 **Figure 5.** Examples of minor and substantial expansion of surface-water extent between

historically dry and historically wet points in time. PHDI: Palmer Hydrological Drought Index.





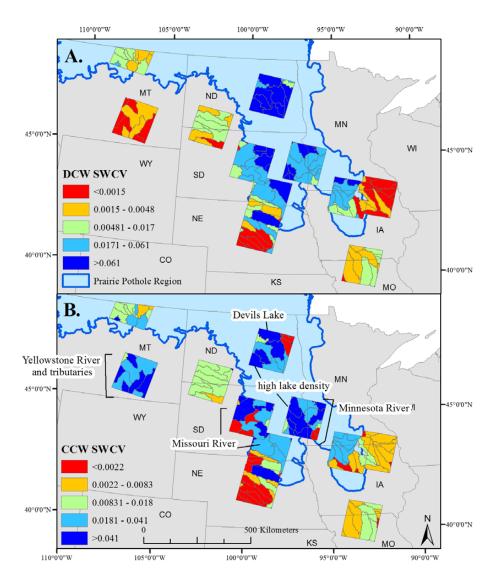
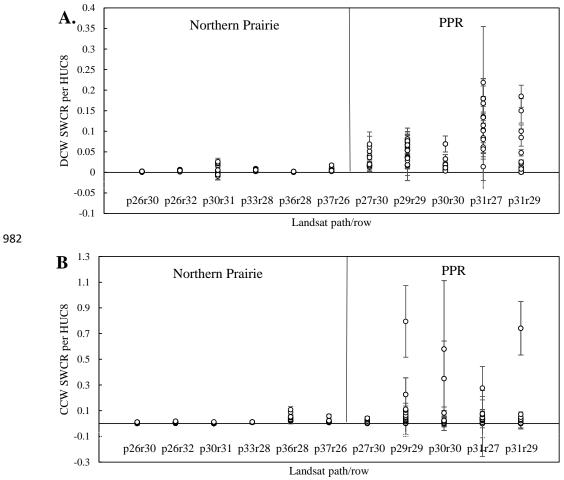




Figure 6. The spatial distribution of the Surface Water Climate Variable (SWCR) values from
the statistical relationships between available water, defined as precipitation minus potential
evapotranspiration accumulated over the previous 9 months, and surface-water extent. Greater
SWCR values indicate greater change in surface-water extent with increased available water.
Surface-water extent was divided between A) disconnected surface water (DCW), or surfacewater extent disconnected from the stream network, and B) continuously connected water
(CCW), or surface-water extent connected to the stream network.







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Figure 7. Distribution of Surface Water Climate Response and standard error values organized
by Landsat path/row and primary path/row location, i.e., the Northern Prairie or the Prairie
Pothole Region (PPR) for A) surface water that is disconnected from the stream network (DCW),
and B) surface water that is connected to the stream network (CCW). HUC8: 8-digit
Hydrological Units

989





## 991 Appendix

- 992 Table 1. A complete list of Landsat TM images used in the analysis and the corresponding
- 993 Palmer Hydrological Drought Index (PHDI).

Landsat	Date	PHDI	Landsat	Date	PHDI	Landsat	Date	PHDI
path/row			path/row			path/row		
p26r30	1989 170	-4.29	p30r30	1990 121	-4.70	p31r29	1989 109	-1.62
p26r30	1989 186	-4.29	p30r30	1989 294	-4.66	p31r29	2003 196	-1.22
p26r30	1988 296	-4.15	p30r30	1989 110	-3.47	p31r29	2004 279	2.52
p26r30	1996 222	-0.24	p30r30	1991 236	-2.79	p31r29	1999 121	5.19
p26r30	1987 117	0.06	p30r30	1988 148	-1.23	p31r29	2011 154	6.55
p26r30	1996 142	0.30	p30r30	2002 122	-1.12	p31r29	2010 167	6.94
p26r30	2010 148	1.10	p30r30	2013 184	-0.94	p31r29	2010 279	8.63
p26r30	2006 153	1.17	p30r30	2003 141	0.26	p33r28	1988 249	-5.68
p26r30	2008 95	2.82	p30r30	2003 285	0.88	p33r28	1990 254	-3.87
p26r30	1993 133	3.95	p30r30	1993 161	5.40	p33r28	2008 112	-2.86
p26r30	1993 277	6.92	p30r30	2011 211	6.49	p33r28	1988 137	-2.47
p26r32	1988 264	-4.18	p30r30	2011 179	6.87	p33r28	2005 135	-2.35
p26r32	2000 105	-3.03	p30r30	2010 288	8.93	p33r28	2003 146	-1.78
p26r32	2003 145	-2.98	p30r31	2002 250	-4.62	p33r28	2005 263	-0.62
p26r32	1989 266	-2.92	p30r31	2000 269	-3.75	p33r28	1998 148	0.22
p26r32	1991 288	-1.88	p30r31	2000 173	-2.66	p33r28	2006 106	0.36
p26r32	1991 96	0.55	p30r31	1990 105	-2.63	p33r28	1998 260	0.70
p26r32	2007 108	0.74	p30r31	2003 141	-2.46	p33r28	1995 188	4.09
p26r32	2002 158	1.59	p30r31	1990 297	-2.45	p33r28	1997 129	5.11
p26r32	1994 136	2.76	p30r31	1990 137	-2.43	p33r28	2015 67	5.37
p26r32	1993 133	3.66	p30r31	2003 221	-2.41	p33r28	2014 160	5.61
p26r32	1994 104	3.79	p30r31	2000 221	-2.38	p33r28	2014 256	9.15
p26r32	2010 100	4.06	p30r31	2000 125	-2.05	p36r28	1988 222	-6.07
p26r32	2008 271	5.07	p30r31	2002 122	-1.84	p36r28	2002 212	-5.14
p26r32	2010 228	5.90	p30r31	2005 178	1.58	p36r28	2004 154	-4.72
p27r30	1988 239	-4.52	p30r31	1986 174	2.19	p36r28	2004 282	-4.29
p27r30	1989 161	-4.34	p30r31	1994 148	3.63	p36r28	2003 135	-2.38
p27r30	2003 280	-1.32	p30r31	1994 260	4.12	p36r28	1985 149	-2.04
p27r30	2002 141	-1.25	p30r31	2011 179	5.22	p36r28	1989 112	-1.94
p27r30	2003 104	1.44	p30r31	2009 173	5.29	p36r28	2013 178	-0.91
p27r30	2008 182	3.03	p31r27	1990 160	-4.12	p36r28	1993 91	-0.89
p27r30	1992 266	3.22	p31r27	2006 252	-3.32	p36r28	2013 242	-0.42
p27r30	1992 122	4.29	p31r27	1991 163	-2.45	p36r28	1998 121	1.67
p27r30	1993 172	6.52	p31r27	1992 118	-1.93	p36r28	2008 181	1.70
p29r29	1990 130	-3.55	p31r27	1999 121	2.01	p36r28	1996 244	2.06
p29r29	2003 118	-2.01	p31r27	2007 255	2.41	p36r28	1996 100	3.81
p29r29	2002 323	-1.69	p31r27	1997 195	2.72	p36r28	1993 235	5.17
p29r29	1991 133	-0.69	p31r27	2005 169	3.06	p36r28	1994 142	
p29r29	1992 136	1.35	p31r27	2009 244	3.28	p37r26	1988 213	-5.70
p29r29	2006 286	2.30	p31r27	2004 279	4.38	p37r26	2006 246	-3.41
p29r29	1998 120	2.77	p31r27	2001 190	4.46	p37r26	1994 261	-2.54
p29r29	2005 91	3.15	p31r27	1995 270	5.97	p37r26	2008 108	-2.37
p29r29	2006 94	4.20	p31r27	2010 279	6.43	p37r26	2002 171	-1.85
p29r29	2001 128	4.47	p31r27	2011 186	6.61	p37r26	1991 141	0.14
p29r29	1997 165	5.05	p31r27	1994 299	7.03	p37r26	2009 142	0.26
p29r29	1995 288	5.71	p31r27	2011 266	8.92	p37r26	1995 168	1.35





p29r29	2011 284	5.88	p31r29	2006 172	-3.49	p37r26	1995 264	1.68
p29r29	2010 105	6.19	p31r29	1989 189	-3.38	p37r26	1987 162	2.15
p29r29	1993 266	6.86	p31r29	2004 135	-2.66	p37r26	1991 269	2.26
p29r29	2011 156	8.37	p31r29	1989 269	-2.31	p37r26	1994 101	2.76
p29r29	2010 281	9.63	p31r29	2003 100	-2.24	p37r26	2013 169	3.40
			p31r29	2003 132	-1.84	p37r26	2011 276	7.32
			p31r29	1990 96	-1.65	p37r26	2011 212	9.14

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