

**Reconstructing the past and modeling the future of
wetland dynamics under climate change**

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Abstract

Reconstructing the past and modeling the future of
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Wetland ecosystems are widely considered to be highly sensitive to climate change. However, scientific capacity to model climate impacts to wetlands has been hampered by the lack of accurate maps showing the spatial distribution of wetlands and data on their historical hydrological dynamics. Though these data may exist for particular wetlands, there are no broad scale datasets of wetland location and long-term hydrological dynamics. Remote sensing has been an important vehicle for mapping change to wetlands, but generally at spatial or temporal scales that do not capture the variability necessary for linking climate to wetland hydrodynamics. This data limitation and lack of methods have restricted research on how changes in climate will impact wetland hydrology to explorations of limited scope.

The goal of this PhD was to characterize and model historic and future climate impacts to dynamics of wetland hydrology (i.e. inundation quantity, frequency, timing and duration) across the Columbia Plateau ecoregion. To achieve this goal, I developed new remote sensing methods

to map and reconstruct wetland dynamics for thousands of individual wetlands at finer temporal and spatial resolutions than previously available (Chapter 1 and 2).

In Chapter 1, I combined high-resolution aerial photographic imagery and a time series of Landsat satellite imagery to reconstruct wetland inundation patterns for individual wetlands from 1984 – 2011 in Douglas County, WA, USA. A key component of this method was the ability to measure fine scale changes (<30m) in surface water area using a sub-pixel technique called spectral mixture analysis. In Chapter 2, I adapted these methods so they could be scaled up to large extents without the computer processing requirements and technical challenges of using aerial imagery. In order to do this, I identified wetlands, not from the spectral and spatial characteristics one can derive out of aerial imagery as in Chapter 1, but instead using their temporal pattern of flooding and drying derived from the time series of Landsat satellite imagery. Using the methods developed in Chapter 1 and Chapter 2, I mapped and reconstructed wetland hydrodynamics for wetlands in the Columbia Plateau ecoregion, far surpassing any existing measurements of wetland hydrology in sample size ($n= 5,382$), temporal richness (~ 23 days), and temporal extent (27 years).

Finally, in Chapter 3 I used this novel dataset to map changes in wetland hydrology across the Columbia Plateau identifying areas undergoing change. Additionally, I developed wetland-specific regression models to understand the relationship between climate and wetland hydrology, which I used to forecast changes to wetland hydrology under climate change. Beyond the technical analyses, an additional important part of the process for Chapter 3 was working

with wetland practitioners from start to finish to ensure the data developed is both useful and used.

The findings of this research suggest that wetlands in the Columbia Plateau are hydrologically variable with each wetland falling along a continuum from those driven primarily by surface water (i.e. precipitation, evaporation, and surface runoff) to those driven primarily by deep groundwater sources. The location of each wetland along this continuum, which I was able to approximate, varies greatly throughout the region, but follows a defined spatial pattern related to underlying geologic processes. Where a wetland falls along the groundwater to surface water continuum largely determined historical changes in inundation levels and how a wetland will respond in the future under climate change. In general, water levels in groundwater driven wetlands have typically decreased since 1984, whereas water levels in surface water driven wetlands have increased or stayed at similar levels over the same period. However, under the climate change scenario selected (ECHAM5 A1B) the results from the wetland-specific regression models suggest that groundwater driven wetlands will increase in water levels and dry less frequently. On the other end of the wetland continuum, surface water wetlands will decrease in surface water levels, dry more frequently, dry earlier in the season, or have little change.

The results of this PhD provide an example of how remote sensing can deliver the fine scale detail and broad temporal and spatial extent necessary to model complex ecosystem dynamics. This knowledge is being used to inform the development of strategies to conserve the biodiversity supported by these systems, and prioritize and help stratify wetlands for further study and conservation action in the Columbia Plateau.

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Introduction and Rationale

Wetlands are sometimes defined as the halfway world between terrestrial and aquatic ecosystems. They exist along a continuum from intermittent wetlands that flood for only a portion of the year in all but the wettest conditions, to permanent ponds that contain water in all but the most severe droughts (Smith 2001; Mitsch and Gosselink 2007). Plant and animal species have adapted to the unique and variable patterns of flooding and drying in different wetlands, and as a result, wetlands support high levels of biodiversity and an array of unique species across many different types of landscapes (Snodgrass et al 2000; Comer, P., K. Goodin, A. Tomaino, G. Hammerson, G. Kittel, S. Menard, C. Nordman, M. Pyne, M. Reid, L. Sneddon 2005). In addition, wetlands provide wide ranging ecosystem services for human society, including water storage & filtration, nutrient cycling, carbon sequestration, agriculture, & recreation value (Arnell and Liu 2001; Zedler and Kercher 2005). Despite their value, over 50% of wetlands worldwide have been lost through draining and filling (Davidson and Finlayson 2007; Davidson 2014). Remaining wetlands are surrounded by an increasingly modified landscape affecting both the condition and function of wetlands (Tiner 2009; Calhoun et al 2016).

Exacerbating current stressors and providing an additional conservation challenge is the growing scientific consensus that wetlands are especially sensitive to climate change (Larson 1995; Johnson et al 2005; Ryan et al 2014; Lee et al 2015). Small changes in precipitation and temperature may substantially alter both the quantity of water and the pattern of flooding and drying within a wetland, which in turn impacts the composition of species and the ecosystem services they provide (Euliss et al 2014; Carter Johnson et al 2016). This is particularly true for arid regions, such as the Columbia Plateau, which are water limited. While a single wetland may provide only a small fraction of the ecosystem services and aquatic habitat in a region, collectively they cover a substantial area and provide a relatively large number of ecosystem services in comparison with other types of aquatic or terrestrial habitat (Downing 2010; Downing et al 2014; Calhoun et al 2016) (**Figure 1**).



Figure 1. Example of an oblique view (left) and an aerial view of depressional wetlands in the Columbia Plateau.

Despite the importance of understanding climate change impacts to wetlands, we know relatively little about how wetlands will respond to climate change. The challenges inhibiting climate modeling of these systems are two-fold: 1) Wetlands are highly dynamic, variable systems and 2) data on the hydrologic regime of wetlands needed to calibrate models of climate impacts are limited to small sample sizes, infrequent observation intervals, and limited spatial and temporal extents (Lee et al. 2015). An additional challenge exists in linking climate models developed for large spatial extents with hydrologic changes at smaller scales relevant to natural resource management and planning.

These data limitations have prevented assessment of regional trends over time, including shifts in the relative coverage of different wetland types and changes in wetland function. While loss of a single wetland may be insignificant, collectively loss of wetland function and condition have been ecologically detrimental (Calhoun et al 2016). This lack of data and techniques to assess wetland change has hindered research, management and planning for some time. The need amongst natural resource managers and conservation planners – who have identified wetlands as essential ecosystems for decades – is now amplified by increasingly common mandates to plan for climate change. Even in areas where detailed climate change projections are available, it is difficult (and sometimes impossible) to translate this information to assess impacts on specific wetlands, because the necessary data at this finer scale are unavailable. This was a problem

highlighted by land managers across the Columbia Plateau. As a result, although general strategies exist for reducing impacts of climate change on wetlands, on-the-ground efforts are seriously hindered by a lack of basic information to understand local manifestations of climate impacts and therefore where and which strategies to implement with some reasonable expectation of success.

Research Goals and Objectives

The goal of this dissertation is to develop new remote sensing methods that allow for mapping wetland locations and hydrodynamics at finer spatial and temporal scales than previously available. I then used resulting datasets to measure changes in historical water levels and to analyze the future effects of projected climate changes on wetland hydrodynamics across the entire Columbia Plateau ecoregion.

The objectives to meet this goal are the following:

1. Develop new remote sensing techniques to reconstruct wetland surface water hydrographs, detailing flooding and drying patterns at fine spatial scales (<30m), from 1984 – 2011 (Chapter 1).
2. Develop new remote sensing techniques to scale methods developed in Chapter 1 up to cover a broad extent by identifying and mapping wetlands using their temporal pattern of flooding and drying derived from a time series of Landsat satellite imagery. (Chapter 2).
3. Measure historical changes in wetland surface water area and forecast changes to the hydrodynamics of wetlands under climate change. (Chapter 3).

Background

Wetland Hydrology

Wetlands represent many diverse and distinctive ecosystems united by the common fact that their dynamics are fundamentally driven by fluctuating availability of water. The hydroperiod, defined as the timing and duration of flooding, is the most important determinant in the

establishment and maintenance of specific wetland habitat types and the services that they provide (Babbitt 2005; Tavernini et al 2005; Mitsch and Gosselink 2007; Correa-Araneda et al 2012). Wetland plants and animals are specifically adapted to the hydroperiod having developed mechanisms to deal with the timing and duration of flooding within a wetland.

Wetland dynamics can occur on daily, seasonal, and long-term time scales, with enormous variation in the pattern and periodicity of their fluctuations. The hydrologic regime of inland wetlands generally fall along a continuum from those driven by surface water to those driven by groundwater sources and thus operate primarily at seasonal and multi-year time scales. The position along this continuum can shift within a single season or slowly over multiple years due to time-varying surface and subsurface flows and deeper groundwater flowpaths (Rains et al 2015).

Because of the complex relationship between hydrologic inputs (i.e. groundwater, surface water) and surrounding geophysical features (e.g. basin size, soil types, geology), wetlands even in close proximity to each other can show very different hydrologic behavior. The cumulative effects of abiotic and biotic factors can interact and their effects are therefore difficult to measure and model independently. In general, surface water wetlands respond to changes in precipitation and evapotranspiration, which fluctuate greatly at seasonal scales. Groundwater dependent wetlands tend to operate at multi-year time scales, due to a higher water storage ability.

The concept of the wetland continuum set out by Euliss et al. (2004) provides a system that classifies wetlands along two axes based on the hydrologic relationship to groundwater and the hydrologic relationship to atmospheric water (i.e. surface water). The wetland continuum differs from other classifications system that classify wetlands by their hydrologic regime, by recognizing that wetland processes are not static, but instead dynamic. This classification system can predict the biological expression of the drought and deluge cycle inherent in many climates and is useful in conceptually understanding how wetlands will respond to climate. While the concept of the wetland continuum is useful in assessing climate change risks to wetlands, it is not often used in practice, in large part because it is difficult to locate a wetland along this continuum.

The high spatial and temporal variability within and among wetlands makes study of these ecosystems particularly challenging. Few studies have related the pattern of flooding and drying to climate variables, largely because the data are unavailable. Those who have looked at changes in surface water have done so at either landscape scales relating climate variables such as precipitation and temperature to longer-term indices such as the Palmer Drought Severity Index (Huang et al 2011) . Others have correlated climate variables as a simplified binary response; flooded or dry (Chandler et al 2016). Lee et al. (2015) related variables derived from the physically based hydrologic model (VIC - Variable Infiltration Capacity (VIC) model), which simulates water balance variables to multiple years of montane wetlands and found good correlation to modeled soil moisture levels in the top and bottom soil layers. This demonstrates that a finer-scale, more mechanistic approach to understanding wetland dynamics may be feasible and is worth exploring for other wetland types.

Wetlands and Climate Change

A commonly cited theory is that the vulnerability of wetlands to climate change fall between two extremes along the wetland continuum: those dependent primarily on surface water for their water supply, which are highly vulnerable, and those that receive their water supply from groundwater, which are thought to be more strongly buffered from climate effects (Winter 2000; Euliss et al 2004). Winter et al. (2001) expanded upon this theory to develop the concept of hydrologic landscapes, categorized by land-surface form, geology, and climate, which can be used to generally assess where a wetland falls along this continuum, and thus how it may be influenced by climate change. Winter broadly classified the hydrologic landscape into mountainous, plateau and high plain, broad basins of interior drainage, riverine, flat coastal, and hummocky glacial and dune, assigning varying levels of climate vulnerability to each landscape class. Wolock et al. (2004) and Wigington (2012) further detailed the hydrologic landscape unit through statistical analysis using a variety of abiotic factors such as land-surface form, geologic texture (permeability of the soil and bedrock), and climate variables that describe the physical and climatic setting. The conceptual framework set out by Winter (2001) and furthered by Wolock et al. (2004) and Wigington et al. (2013) is widely cited, yet it has not been tested in the context of wetlands. This is likely due to the absence of long-term large-scale baseline data on wetland dynamics and the challenge of modeling groundwater processes.

While useful, these studies could only model climate change impacts in a generalized way, without addressing the complex relationship of wetlands to groundwater and surface water sources and how that relationship varies across the landscape. The few studies forecasting the impacts of climate change on wetlands have been limited in some way; a small sample size, geographic extent, frequency of observations, and duration of study, thus are unable to track the extent of spatial and temporal variability of wetlands (Poiani et al 1996; Arnell et al 2001; Werner et al 2013; Ryan et al 2014). Poiani et al. (1996), for example, used a long-term dataset which included detailed fine-scale surface and subsurface hydrologic processes from one North Dakota wetland and modeled the response of climate change through development of a daily water balance model (WETSIM 2.0). Johnson et al. (2005) used an extension of WETSIM model, WETLANDSCAPE, parameterized by 10 wetlands, to predict the shift in the distribution of semi-permanently flooded wetlands within the prairie potholes region using an interpolation method. Using a similar approach, Johnson et al. (2016) found that wetlands in the prairie potholes region have a non-linear response to climate change. They found that wetlands that dried early in the season under current climate conditions would be less impacted by any increases in temperature, and corresponding increase in evapotranspiration rates, than those that currently dried later in the summer or early fall. For a comprehensive review of the research findings conducted in the Prairie Potholes Region see Johnson et al. (2016).

Lee et al., (2015) used field measurements of hydroperiod data collected over multiple years and soil moisture variables from the VIC hydrologic model to predict hydrologic response in wetlands. They found that climate-induced changes to key driving variables (reduced snowpack, higher evapotranspiration, extended summer drought) will result in earlier and faster drawdown in Pacific Northwest montane wetlands. They predicted that these changes will cause systematic reductions in water levels, shortened wetland hydroperiods, and increased probability of drying. For my dissertation I build upon Lee et al.'s method using the VIC model outputs, by extending the hydrologic data to longer temporal and spatial extents. In doing so, longer term groundwater patterns emerged, requiring the addition of new climate variables simulating the groundwater response to climate.

Table 1. Summary of Studies Projecting Climate Change Impacts to Wetlands

Study	Study Area	Data <ul style="list-style-type: none"> • # of wetlands • # of observations • time span 	Method	Key Findings
<i>1.. Vulnerability of Northern Prairie Wetlands to Climate Change</i> (JOHNSON et al 2005)	Prairie Potholes Region (PPR)	<ul style="list-style-type: none"> • 1 wetland • Systematic (specific # of obs. not stated) • 1979 - 2005 	WETLANDSCAPE (WLS) , a climate- driven, process-based, deterministic model of prairie wetland complexes.	Under a drier climate waterfowl habitat will shift to eastern region of PPR where wetlands due to the presence are more disturbed and drained.
<i>2.. Prairie Wetland Complexes as a Landscape Functional Units in a Changing Climate</i> (Johnson et al 2010)	Prairie Potholes Region (PPR)	<ul style="list-style-type: none"> • 10 wetlands • 13 – 16 years, (specific # of obs. not stated) • 1992 - 2005 	WETLANDSCAPE (WLS)	Wetlands in PPR will be the most vulnerable to climate change in the following increasing order: temporary, semi-permanent, seasonal. In general wetlands in the west will get drier than wetlands in the east.
<i>3.. Evidence for 20th century climate warming and wetland drying in the North American Prairie Pothole Region.</i> (Werner et al 2013)	Prairie Potholes Region (PPR)	<ul style="list-style-type: none"> • 9 basins • 13 – 16 years, (specific # of obs. not stated) • 1992 - 2005 	WETLANDSCAPE (WLS)	Modeled wetlands in the PPR’s western Canadian prairies show the most effects: a recent trend toward shorter hydroperiods and less dynamic vegetation cycles.
<i>4. Non-linear responses of glaciated prairie wetlands to climate warming Climatic Change.</i> (Carter Johnson et al 2016)	Prairie Potholes Region (PPR)	<ul style="list-style-type: none"> • 10 wetlands • Frequent, (specific # of obs. not stated) • 1993 – 2010 	WETLANDSCAPE (WLS)	Wetlands in the PPR would lose function beyond climate warming of about 1.5° -2.0 °C above present baseline temperature.

<p>5. <i>Projecting the Hydrologic Impacts of Climate Change on Montane Wetlands</i> (Lee et al 2015)</p>	<p>Pacific Northwest mountains, USA</p>	<ul style="list-style-type: none"> • 121 wetlands • 3-6 obs/yr • 1992, 2000, 2012, 2003 – 2006, 2003 & 2006, 2033 – 2007. (Diff. for each location) 	<p>Wetland specific regression model correlating wetland hydrology measured using Landsat time series and the VIC hydrologic model, which we then forecasted and hindcasted</p>	<p>Changes in snowpack and higher rates of evapotranspiration will result in earlier and faster drawdown in montane wetlands, leading to systematic reductions in water levels, shortened wetland hydroperiods, and increased probability of drying</p>
<p>6. This PhD</p>	<p>Columbia Plateau ecoregion, USA</p>	<ul style="list-style-type: none"> • 1,735 wetlands • 100 – 200 observations • 1984 - 2011 	<p>Wetland specific regression model correlating wetland hydrology measured using Landsat time series and the VIC hydrologic model, which we then forecasted and hindcasted</p>	<p>Wetlands are highly variable systems existing along a continuum from groundwater to surface water driven. In general surface water driven wetland will dry versus groundwater driven wetlands which will get wetter.</p>

Remote Sensing of wetlands

Landscape-level hydrologic data for wetlands is scarce because tracking changes in wetland water levels over weeks and months requires the installation of expensive monitoring equipment or visiting sites many times a year for several years (Lee et al 2015). Remote sensing provides an opportunity to dramatically increase the sample size and quantify ecosystem changes at the scale of individual wetlands, while preserving the broad spatial coverage necessary for landscape-scale analyses (Skidmore et al 2011; Wulder et al 2014). However, mapping the hydroperiod of wetlands offers several challenges to remote sensing analysts. Most remote sensing tools are limited by the spatial, temporal, or spectral resolution of the sensor used for analysis (Ozesmi and Bauer 2002; Wulder et al 2014). For example, in order to map wetlands analysts typically use high resolution aerial imagery (< 1 meter) (Tiner 1990), but repeat coverage is lacking. This aspect of remote sensing platforms has generally limited high-resolution remote sensing of wetlands to detecting change between a few specific dates (Munyati 2000; Soliman and Soussa 2011). The frequency of aerial image acquisition by the U.S. Department of Agriculture’s National Aerial Imagery Program (NAIP) typically occurs every two years. Although prior to XXXX it was less frequent. Although useful in detecting the

location of wetlands and establishing some of their broad characteristics, change detection between two specific dates does not capture wetland hydrodynamics in sufficient detail, and additional information with greater temporal resolution is needed to place such observations in context. For example, does the wetland dry each year in the late summer? Unless the dates when remotely sensed images are available happen to coincide with these particular hydrologic features of interest such questions cannot be answered. In addition, observed changes in water levels are dependent on the specific hydrologic variability observed in a particular sequence of years and could represent normal behavior or extreme conditions. Ephemeral wetlands observed in a relatively wet period, for example, might appear to be intermediate wetlands with a longer hydroperiod. Conversely intermediate wetlands observed in a dry period might appear to be ephemeral wetlands. Thus additional measurements and/or retrospective simulations over a longer period of time are needed to establish an accurate probability distribution describing the hydrologic behavior of a particular wetland, which in turn informs its sensitivity to climate change (Lee et al. 2015). Conversely, sensors with a higher temporal resolution, such as Landsat or MODIS, have a coarse pixel resolution that is often inadequate to map changes to small, ecologically important wetlands, which are frequently the most common wetland type on the landscape (Tiner 1990; Downing et al 2014).

The traditional focus of remote sensing has been on single sensor analysis, using only one remotely sensed data source (Wulder et al 2014). However, due to improvement in computer processing, new software developments, and available techniques in recent years there has been a trend towards developing hybrid products that combine data from multiple sensors to improve the spatial, temporal, or spectral resolution. The research proposed here combines data from aerial imagery and satellite imagery to map wetland locations and hydrodynamics at finer spatial and temporal scales than previously available. This approach can also be used to study other ecosystems, for example meadows, to identify and track ecosystem dynamics through time.

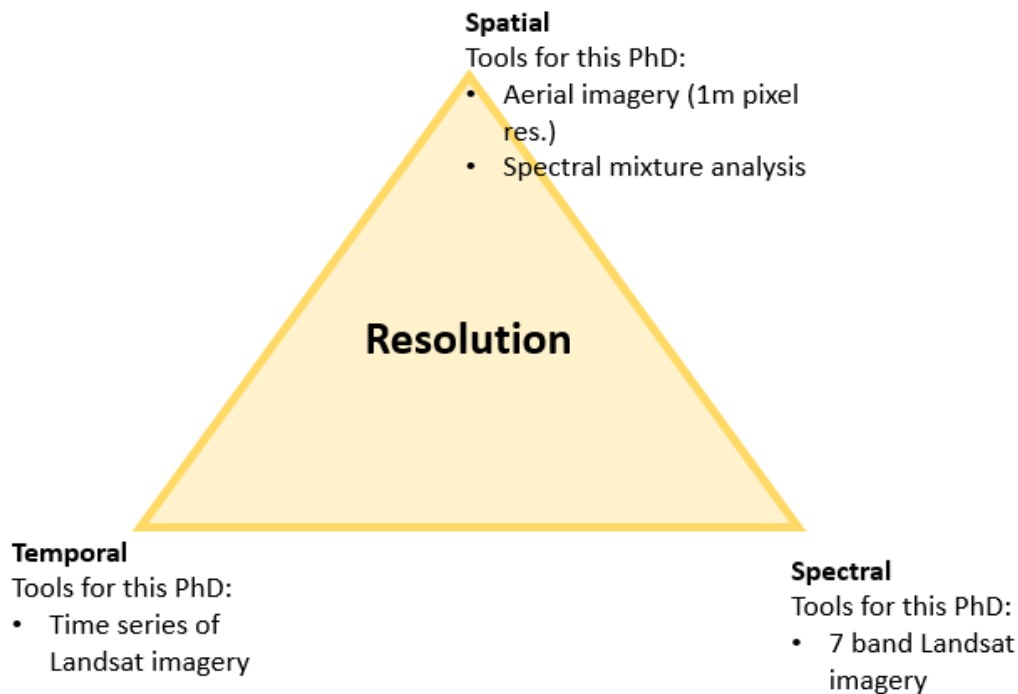


Figure 2. Three types of high-resolution domains in remote sensing; temporal, spatial, & spectral and the high-resolution tools used for this PhD to model wetland dynamics.

Another barrier to modeling wetland dynamics using remote sensing is that pixel-based approaches for analyzing change through time have been, and continue to be, the dominant paradigm in the analysis of remotely sensed data (Blaschke 2010). Pixel-based approaches use the spectral signature (color) of individual pixels instead of grouping pixels into objects. The “pixel-centric” approach does not allow for the structural parameters (i.e. color, texture, pattern, shape, temporal) of the image to be taken into consideration (Blaschke et al 2014). For remote sensing analysts, it also creates a paradigm of thinking about landscapes in terms of pixels, rather than consisting of patches that more closely reflect ecologically meaningful units (Blaschke and Strobl 2015). Thus, most remote sensing studies that examine temporal patterns of wetlands have done so by tracking changes at the individual pixels (Gómez-Rodríguez et al 2010; Collins et al 2014; Reschke and Hüttich 2014) or have summarized changes for all pixels within an entire landscape (Beerli and Phillips 2007; Huang et al 2011; Huang et al 2014). Neither of these approaches capture the spatiotemporal variability inherent in the hydrodynamics of wetlands.

Object based image analysis (OBIA) is a relatively new technique in the field of remote sensing, but is built upon older photogrammetry methods and computer technologies (Strobl and Blaschke 2001). Essentially, the OBIA process attempts to mimic human pattern recognition by first grouping raster pixels into objects, using a process called segmentation. Once an image is segmented the user can characterize the object of interest using spectral, spatial, and temporal characteristics of the object. Object based approaches can summarize information at the object or patch scale, making it possible to track specific changes in the object through time. OBIA also provides a mechanism for easily combining multiple datasets of varying spatial, temporal, and spectral resolution. Here I used OBIA techniques to integrate multiple datasets (Figure 2), with the objective of improving the spatial, temporal, and spectral resolutions of wetland observations over a large geographic area in Eastern Washington.

Summary of Chapters

Chapter 1. Reconstructing semi-arid wetland surface water dynamics through spectral mixture analysis of a time series of Landsat satellite images (1984 – 2011)

We used spectral mixture analysis (SMA) of a time series of Landsat satellite imagery to reconstruct surface-water hydrographs for 750 wetlands in Douglas County, Washington State, USA, from 1984 to 2011. SMA estimates the fractional abundance of spectra representing physically meaningful materials, known as spectral endmembers, which comprise a mixed pixel, thus providing sub-pixel estimates of surface water extent. Endmembers for water and sage steppe were selected directly from each image scene in the Landsat time series, whereas endmembers for salt and wetland vegetation were derived from a mean spectral signature of selected dates spanning the 1984 – 2011 timeframe. This method worked well ($R^2=0.99$) for even small wetlands ($<1800 \text{ m}^2$) providing a broad scale dataset of reconstructed surface-water hydrographs for wetlands across our study area at an average frequency interval of 23 days.

Chapter 2. Exploring the temporal dimension in object-based image analysis to improve remotely sensed observations of wetlands

Research using object-based image analysis has typically focused on the spectral and spatial domain to identify and classify objects, but the temporal domain is only rarely explored. For some objects, which are spectrally similar to other landscape features, their temporal pattern may be their sole defining characteristic. Here, we developed a straightforward way to identify wetlands using a time series of Landsat imagery by building a Random Forest model using each image observation as a variable in our model. We also found that, up to a point, using a higher number of image observations improved classification accuracy. While time series analysis has been part of pixel-based remote sensing for many decades, with improved computer processing and increased availability of time series datasets (e.g. the Landsat archive we used here) it is now much easier to incorporate time series data into object-based image analysis classification schemes.

Chapter 3. Projecting climate change impacts on wetland hydrology in the Columbia Plateau ecoregion

The goal of this project was to provide just such understanding, in the form of wall-to-wall maps of wetlands across the region, coupled with detailed 30-year hydrographs of historical (1984-2014) fluctuations in water extent for each of those wetlands, and similar, modeled 30-year hydrographs for fluctuations expected under future (2070-2099) climate. We developed these products with remote sensing methods using 581 historical Landsat images to map surface water extent of wetlands. Extending research reported by Lee et al. (2015) we combined these data with simulations from the Variable Infiltration Capacity (VIC), a macro-scale hydrological model that simulates soil moisture and other water balance components as a function of climate, land cover, and soils. We developed statistical models that captured the relationship between the remotely-sensed surface water extent and the VIC metrics produced using historical climate information. By running VIC using projected future climate, and then applying our statistical models to the resulting soil moisture metrics, we were able to make projections of expected water extent under end-of-the-century climate.

The hydrologic behavior in eastern WA is influenced by past glacial events and deposits, and also by human development activity over the past hundred years, especially agriculture. Three regions are important in the context of this PhD; the glaciated region, the channeled scablands, and the Columbia Basin Irrigation Project (Figure 2). The northwestern part of the Columbia Plateau was glaciated during the last ice age, approximately 20,000 years ago, which created a topographically complex area with perched aquifers and intricate subsurface flows, and a high density of depressional wetlands. The channeled scablands were created by a series of massive floods between 18,000 and 13,000 years ago, which scoured parts of the Columbia Plateau. The Columbia Basin Irrigation Project (CBP) is an irrigation development project that began bringing water from the Columbia River to agricultural lands in the central region of the Columbia Plateau in the early 1950s. The CBP caused groundwater levels to rise, which in turn supplemented existing wetlands and established new ones. Most of the wetlands in this area are groundwater driven. The Columbia Basin Project intersects with parts of the Channeled Scablands. In these overlapping areas influences from the CBP override the natural conditions.

Materials

Aerial imagery

We used two digital ortho-imagery (2006 and 2011) with 1-m pixel resolution freely available through the National Agricultural Inventory Program (NAIP) rectified to true ground +/- 6 m. The 2006 digital aerial image was a 3-band image (red, green, blue) and was acquired early in the summer of 2006 (exact date unknown), a wet year, when wetland water levels were high (USDA-FSA Aerial Photography Field Office, 2006). The 2011 aerial imagery was a 4-band image (NIR, red, green, blue) and was acquired between 06 Jul 2011 and 07 Jul 2011 (USDA-FSA Aerial Photography Field Office, 2011).

Landsat satellite imagery

We downloaded 581 Landsat Thematic Mapper 4 & 5 satellite images acquired between 1984 and 2011 from the United States Geologic Services GLOVIS website (<http://glovis.usgs.gov/>) using the batch download tool for our time series analysis. Our study area fell on seven Landsat scenes. All downloaded images were processed as Level 1T terrain-corrected products. Because

most wetlands in our study area freeze in the winter months and may be covered in snow, only snow-free images acquired between March 1 and October 30th were selected.

VIC Hydrologic Model

The Variable Infiltration Capacity (VIC) model (Liang et al. 1994) is a physically based hydrologic model that, when driven by precipitation, temperature, and other climatic variables, simulates water balance variables that affect wetland water levels, for each location across the landscape. Input variables therefore include daily meteorological data—precipitation, maximum and minimum daily surface air temperature, and wind speed for each grid cell the model is run on—in addition to soil and vegetation data. Output variables include runoff, baseflow, evapotranspiration, soil moisture at three different soil depths, as well as the snow water equivalent above the surface. The VIC model has been widely used to assess the hydrologic impact of climate change on a number of watersheds in the Pacific Northwest and across the western U.S. (e.g., Hamlet et al., 2013; Tohver et al., 2014; Salathe et al., 2013).

**Chapter 1. Reconstructing semi-arid wetland surface water dynamics
through spectral mixture analysis of a time series of Landsat satellite images
(1984 – 2011)**

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Abstract

Wetlands are valuable ecosystems for maintaining biodiversity, but are vulnerable to climate change and land conversion. Despite their importance, wetland hydrology is poorly understood as few tools exist to monitor their hydrologic regime at a landscape scale. This is especially true when monitoring hydrologic change at scales below 30 m, the resolution of one Landsat pixel. To address this, we used spectral mixture analysis (SMA) of a time series of Landsat satellite imagery to reconstruct surface-water hydrographs for 750 wetlands in Douglas County, Washington State, USA, from 1984 to 2011. SMA estimates the fractional abundance of spectra representing physically meaningful materials, known as spectral endmembers, which comprise a mixed pixel, thus providing sub-pixel estimates of surface water extent. Endmembers for water and sage steppe were selected directly from each image scene in the Landsat time series, whereas endmembers for salt and wetland vegetation were derived from a mean spectral signature of selected dates spanning the 1984 – 2011 timeframe. This method worked well ($R^2=0.99$) for even small wetlands ($<1800\text{ m}^2$) providing a wall-to-wall dataset of reconstructed surface-water hydrographs for wetlands across our study area. We have validated this method only in semi-arid

regions. Further research is necessary to extend its validity to other environments. This method can be used to better understand the role of hydrology in wetland ecosystems and as a monitoring tool to identify wetlands undergoing abnormal change.

1 Introduction

Wetlands are among the most biodiverse ecosystems in the world, due largely to their dynamic hydrology (Mitsch and Gosselink 2007). The hydroperiod, which we define as the pattern of flooding and drying within a wetland, is the most important determinant in the establishment and maintenance of specific wetland habitat types and the species that they support (Babbitt 2005; Tavernini et al 2005; Mitsch and Gosselink 2007; Correa-Araneda et al 2012). Despite the importance of the wetland hydroperiod, it is not well understood (Mitsch and Gosselink 2007), in part because it is time-consuming and expensive to monitor changes in wetland hydrology using field measurements. Landscape-level hydroperiod data are scarce because tracking changes in wetland water levels over weeks and months requires the installation of expensive monitoring equipment or visiting sites many times a year for several years (Ryan et al 2014). However, without broad-scale long-term hydroperiod data it is not possible to adequately monitor changes in the hydrologic regime of wetlands to understand general patterns across different wetland types and to distinguish the difference between natural and abnormal changes to wetland hydrology. Furthermore, without adequate baseline data of the wetland hydroperiod, it is not possible to understand how changes in temperature and precipitation will impact the hydrology, structure and function of wetlands under climate change (Poiani et al 1996; Arnell et al 2001; Werner et al 2013; Ryan et al 2014).

1.2 Wetland definition

We define wetlands using the United States Army Corps of Engineer's definition of wetlands as "those areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions." (Environmental Laboratory, 1987) Shallow lakes and lake fringes meet the above definition within our study area, and therefore, this analysis includes both large and small waterbodies.

1.2 Remote sensing of wetland surface water dynamics

Remote sensing has provided a useful means to study the changes in wetlands through spatially explicit, cost- and time-effective data (Ozesmi and Bauer 2002). However, mapping the hydroperiod of wetlands offers several challenges to remote-sensing analysts. The core challenge is the trade-off between temporal and spatial resolution of remotely sensed imagery. Currently, no one sensor has both the temporal and spatial resolution to detect the fine-scale patterns of wetland change over time, particularly for small wetlands (Tiner 2009; Wulder et al 2014; Gallant 2015).

Landsat imagery with moderate spatial and temporal resolution has widely been used for surface water mapping through hard classification methods (*sensu* Foody, 2000), which classify pixels as either water or non-water. Commonly used classification methods include thematic classification, multi-band indices (e.g. normalized difference water index, NDWI (McFeeters 1996)), single band thresholding, and spectral mixture analysis (Ozesmi and Bauer 2002). These methods have been successfully applied to map surface water changes of large lakes and wetlands (Bryant and Rainey 2002; Castaneda and Herrero 2005; Hui et al 2008; Sener et al 2010; Liu et al 2013; Adams and Sada 2014). However, wetlands that express changes in surface water extent at fine scales (below 30m – the resolution of 1 Landsat pixel) and small wetlands, which we define as wetlands smaller than 5 ha, have received considerably less attention (Ryan et al 2014). This is an issue because in many regions of the world the majority of the landscape is composed of small wetlands (Gilmer et al 1980; Halabisky et al 2011; Downing et al 2014). For high resolution mapping of wetlands analysts typically use high-resolution aerial imagery (<1 m), but repeat coverage is lacking (Tiner 1990). This has limited high-resolution remote sensing of wetlands to detecting change between a few dates (Murkin et al 1997; Dyke and Wasson 2005; Niemuth et al 2006; Hui et al 2008; Liu et al 2013; Adams and Sada 2014).

Although useful, change detection of wetlands under these limitations does not provide enough detail for understanding patterns and dynamics of annual and inter-annual wetland response, much less to determine if measured changes in the surface water extent represent natural year-to-year variability, or abnormal changes in wetland hydrology. Even several dates of aerial imagery

cannot provide enough information to determine the hydrologic regime of a particular wetland necessary for monitoring or future climate modeling.

In order to address this limitation several researchers have used one or more soft classification techniques such as multi-band indices and single band tracking to predict sub-pixel surface water estimates of Landsat imagery (Beerli and Phillips 2007; Gómez-Rodríguez et al 2010; Rover et al 2010a; Huang et al 2011; Frohn et al 2012; Huang et al 2014; Reschke and Hüttich 2014). Soft classification methods do not assign a pixel to one class, but instead provide an estimate of class membership and can be used to measure the sub-pixel surface water area through regression modeling and classification and regression trees (Foody 2000). However, these methods require a large amount of training data from field data or higher resolution imagery from the same time period and are not directly transferable to other study areas (but see Rover, Wylie, & Ji, 2010a).

Spectral mixture analysis (SMA) is a physically based technique which can be used to estimate the percent cover of surface water without the need for extensive training data. SMA estimates the fractional abundance of spectra representing physically meaningful materials, known as spectral endmembers, which comprise a mixed pixel, thus providing sub-pixel estimates of surface water extent (Adams et al., 1986; Adams & Gillespie, 2006). While SMA provides sub-pixel fractions of surface materials, it is commonly used to drive a classification by converting mixed pixels into water or non-water through selection of a threshold value (Shanmugam et al 2006). Frohn et al. (2012) used SMA to identify wetlands at sub-pixels scales, but did not use it to estimate the percent cover of surface water or track changes to surface water through time. While sub-pixel methods can identify the percent cover of surface water they do not provide the location of surface water within a pixel, which makes tracking change over time challenging. To remedy this issue, researchers have either tracked changes of individual pixels (Beerli and Phillips 2007; Gómez-Rodríguez et al 2010; Collins et al 2014; Reschke and Hüttich 2014) or summarized changes for all pixels within an entire landscape (Beerli and Phillips 2007; Huang et al 2011; Huang et al 2014). Table 1 summarizes the key papers that meet one or more of the criteria necessary for high resolution mapping of wetland surface water dynamics.

Table 1: Summary of key papers related to this study’s research objectives (the current paper is added for completeness). In the ‘Key details’ column the codes relate to the following criteria: (1.) Spatial resolution of surface water measurement (2.) Scale used for tracking change: wetland, pixel or landscape (3.) Temporal resolution: seasonal or long-term (4.) Application

Study	Study Area	Data Used	# of Image Dates / Time Span	Method	Key Details
1. (Gómez-Rodríguez et al 2010)	Doñana National Park, Spain	Landsat TM	174 dates 1984 - 2007	Developed a linear model using reflectance of near IR band to predict subpixel fractions of water cover.	1.) <30m 2.) Pixel 3.) Seasonal and long-term 4.) Classified wetland types by hydroperiod and monitored wetland change over time.
2. (Beeri and Phillips 2007)	Missouri Couteau, USA	Landsat TM	31 dates 1997 - 2005	Developed a regression model to identify surface water for waterbodies greater than a half a Landsat pixel.	1.) <30m 2.) Pixel and landscape 3.) Seasonal and long-term 4.) Identified shifts in the distribution of hydroperiod classes within and between years
3. (Huang et al 2011)	Cottonwood Lake, North Dakota, USA	Landsat TM, aerial photos, lidar	26 (Landsat TM), 11 (aerial photos), 1 (lidar)	Developed a complex regression model using Landsat, Palmer Drought Severity Index, and aerial imagery to model surface water for wetlands as small as 0.8 ha.	1.) <30m 2.) Wetland and landscape 3.) Seasonal and long-term 4.) Tracked changes to surface water from modeled result, which is driven by PDSI.
4. (Huang et al 2014)	Chesapeake Bay watershed, USA	Landsat TM, lidar intensity	4 dates 2005 - 2010	Developed a regression model using multiple variables including tasseled cap indices, NDVI, NDWI and Modified NDWI, and an infrared-visible ratio index to predict sub-pixel wetland inundation maps.	1.) <30m 2.) Landscape 3.) N/A 4.) Tracked changes in inundation for a wet, dry, and average year and summarized at the landscape scale.

5. (Reschke and Hüttich 2014)	Western Turkey	Landsat TM	3 dates 2002 – 2003	Mapped sub-pixel fractional wetland type (including water) using a Random Forest algorithm	1.) <30m 2.) Pixel 3.) Seasonal 4.) Classified wetlands by type (i.e. marsh, mudflat, river, water), but not by hydroperiod
6. (Collins et al 2014)	Prairie Potholes, USA	Landsat TM	35 dates 2008 -2011	Used a band ratio (bands 5, 3) to classify pixels as water, non-water.	1.) 30m 2.) Pixel , wetland, landscape 3.) Seasonal and long-term 4.) Measured hydroperiod length of playa wetlands for 3 years and compared it to surrounding land use.
7. (Frohn et al 2012)	Ohio, USA	Landsat TM	2 dates 2002 - 2003	Developed a spectral mixture analysis partial unmixing model to detect sub-pixel inundation levels.	1.) <30m 2.) Pixel 3.) N/A 4.) Identified isolated wetlands as small as ½ Landsat pixel.
8. (Rover et al 2010b)	Alaska, USA	Landsat TM, SPOT-5	one date N/A	Developed a self-trained regression tree using single band and multi band indices to map sub-pixel percent-water maps and compared results to other sub-pixel methods.	1.) <30m 2.) Pixel 3.) N/A 4.) N/A
9. (Niemuth et al 2010)	Prairie Pothole Region, USA	Aerial photos	20 dates 1987–2006	Used a combination of supervised classification and photo interpretation to map surface water area within wetlands.	1.) <8m 2.) Wetland 3.) Long-term 4.) Examined spatiotemporal patterns of wetland inundation.
10. Our method	Douglas Co, WA, USA	Landsat TM	230 dates 1984 - 2011	Developed a 4 endmember spectral mixture analysis	1.) <30m 2.) Wetland 3.) Seasonal and long-term

Aerial photo	model to measure sub-pixel wetland inundation.	4.) Classified wetland types by hydroperiod and monitored wetland change over time.
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What is almost entirely missing from the methods summarized in Table 1 is the ability to track changes to individual wetlands and the temporal detail to monitor both seasonal and long-term changes in wetland hydrology. Only one study that achieved this was Gómez-Rodríguez et al. (2010) in which the authors measured changes in the flooding duration of wetlands by examining how pixel reflectance of the near infrared band changed through time for over 800 temporary ponds spanning a 23-year time period in the Doñana National Park, Spain. Because the authors co-registered images to correct for small pixel misalignments between image scenes they could track changes of surface water extent for pixels within an individual wetland showing a significant trend of hydroperiod shortening likely due to groundwater depletion from agricultural irrigation. However, a challenge with tracking single pixels through time is the labor-intensive and imperfect process of pixel-to-pixel registration and atmospheric correction for multi-date analysis (Dai 1998; Song et al 2001; Wyawahare et al 2009). For some projects, it is not feasible to perform these pre-processing steps on hundreds of images.

We sought to develop a method that mapped surface water dynamics at temporal and spatial scales similar to Gomez-Rodriguez et al. (2010), but with minimal pre-processing. Additionally, we aimed to use this data to reconstruct individual wetland surface water hydrographs, which chart the pattern of flooding within a wetland over time. Here we use the term hydrograph to refer to temporal changes in surface-water extent (area) within a wetland, rather than temporal changes in water depth. This is due to the difficulty of determining water depth from a pixel composed of multiple surface materials.

The goal of this project was to develop a semi-automated tool to map and monitor wetland dynamics for individual wetlands while still covering a broad landscape. Specific objectives of this research were to:

- 1.) Develop a method with minimal pre-processing to estimate surface-water extent for wetlands at scales below 30m.
- 2.) Reconstruct individual wetland hydrographs from 1984 to 2011.
- 3.) Determine if hydrographs could be used to classify wetland types and monitor wetland change over time.

2 Study Area

We chose Douglas County, Washington (WA), located in the Columbia Plateau ecoregion in the Northwest of the United States as our study area (Figure 1) as wetlands are abundant and representative of semi-arid ecosystems common to Western North America. Douglas County is 4,714 km² in size with non-irrigated farming and ranching being the dominant land uses. It is a semi-arid sage steppe ecosystem, receiving an average of 29 cm of precipitation a year. Douglas County is bordered by the Columbia River with a low elevation of 180 m near the river and rising to an elevation of 1,220 m at the top of the plateau. In general, the surface topography of the plateau is subtle and free from shadows resolved at the 30-m Landsat scale. Isolated, depressional wetlands are the dominant wetland type. Wetlands are typically shallow and do not support floating vegetation. Wetland vegetation is restricted to areas that are seasonally flooded, often forming a ring around wetlands that are semi-permanently or permanently flooded. Refill of wetlands in this area is driven by snowmelt occurring in late winter or early spring. As the summer season progresses temperatures increase and precipitation levels decline. Wetlands begin to dry out during this time, and many are completely dry by the end of the summer. Short-term rainfall events are usually localized in nature and occur sporadically during the spring and summer months. Although the direct causes of hydrologic change are not clear due to lack of research, wetlands in the Columbia Plateau generally are known to be stressed from impacts caused by farming, grazing, and reduced groundwater levels.

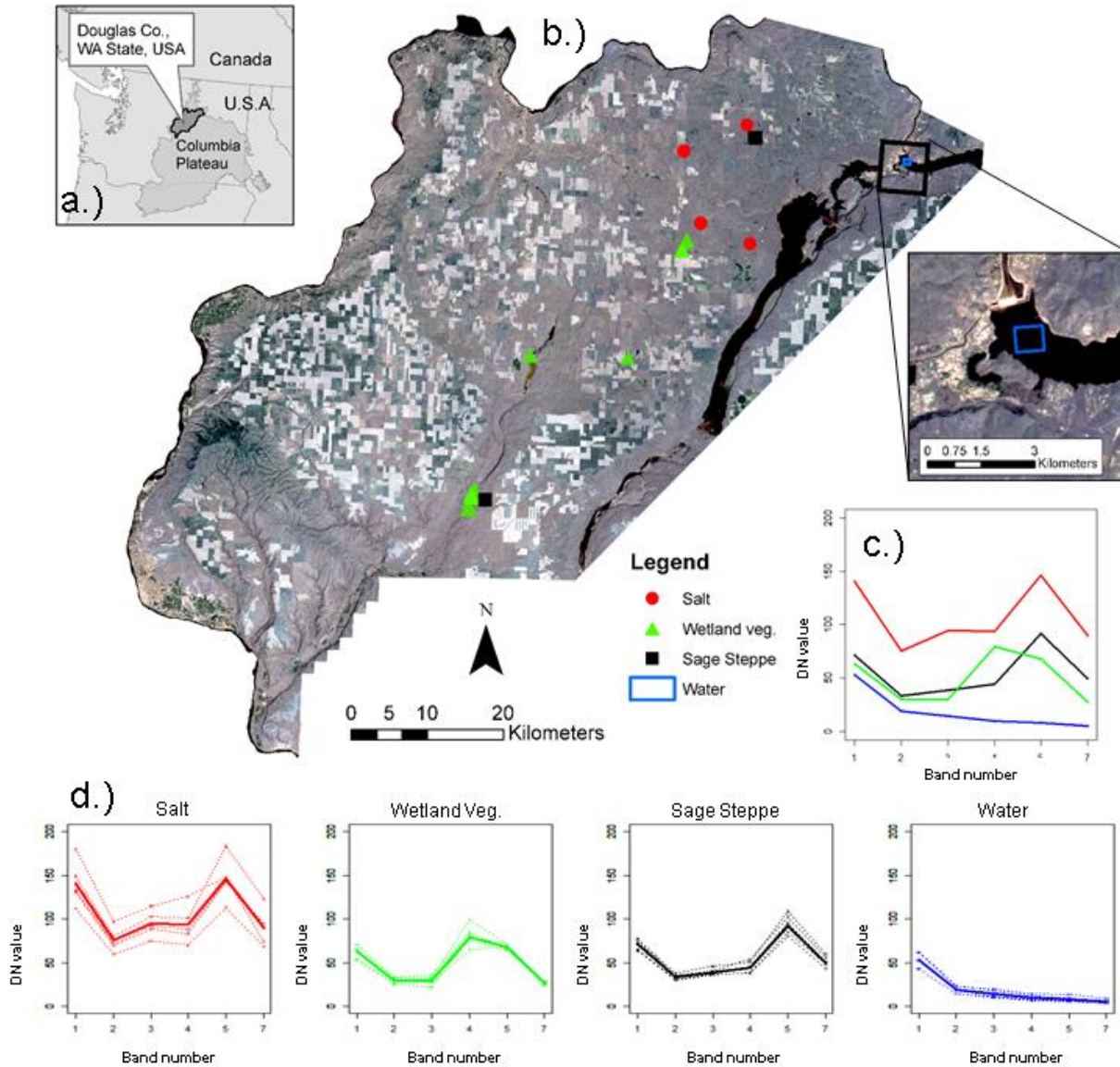


Figure 1: a.) Study area, Douglas County, Washington state, USA. b.) Endmember locations. The background image is a Landsat TM 5 scene acquired on 07 Jul 2011 and was clipped to our study area. c.) The graph represents the four endmembers used; water (blue), salt (orange), wetland vegetation (green), sage steppe (black). d.) Endmember graphs for salt and wetland vegetation from selected dates spanning the 1984 – 2011 timeframe used to derive a mean spectral signature for SMA. The graphs for sage steppe and water represent the image endmembers from the same date selection and illustrate the spectral variability across multiple image dates, but were not used for SMA. Instead, endmembers for water and sage steppe were selected directly from each image scene in the Landsat time series.

3 Materials

3.1 Aerial imagery

We used two digital ortho-imagery (2006 and 2011) with 1-m pixel resolution freely available through the National Agricultural Inventory Program (NAIP) rectified to true ground +/- 6 m. The 2006 digital aerial image was a 3-band image (red, green, blue) and was acquired early in the summer of 2006 (exact date unknown), a wet year, when wetland water levels were high (USDA-FSA Aerial Photography Field Office, 2006). The 2011 aerial imagery was a 4-band image (NIR, red, green, blue) and was acquired between 06 Jul 2011 and 07 Jul 2011 (USDA-FSA Aerial Photography Field Office, 2011).

3.2 Landsat satellite imagery

We downloaded 230 Landsat Thematic Mapper 5 satellite images acquired between 1984 and 2011 from the United States Geologic Services GLOVIS website (<http://glovis.usgs.gov/>) using the batch download tool for our time series analysis. Our study area fell on two Landsat scenes, path 45 row 27 and path 44 row 27. Each image was visually assessed for quality, and only cloud-free images were chosen. All downloaded images were processed as Level 1T terrain-corrected products. Because most wetlands in our study area freeze in the winter months and may be covered in snow, only snow-free images acquired between April 1 and October 30th were selected.

Table 2: Materials

Datasets	Spatial Resolution	Temporal Resolution	Source
2006 digital aerial imagery	1 m	1- 3 years	United States Department of Agriculture, National Agriculture Inventory Program
2011 digital aerial imagery	1 m	1 -3 years	United States Department of Agriculture, National Agriculture Inventory Program
Landsat TM 5	30 m	16 days	United States Geological Survey http://glovis.usgs.gov/

4 Methods

We identified wetlands in our study area using an object-based image analysis classification of high-spatial-resolution aerial photography (Sections 4.1). For each identified wetland, we estimated the sub-pixel surface water area (m^2) from a four-endmember spectral mixture analysis (SMA) of Landsat TM imagery (Section 4.2.1, 4.2.2). We then validated the SMA model for 750 wetlands by comparing surface water area from one Landsat image to wetland surface water area delineated from a matching date of high resolution aerial imagery (Section 4.2.3). Next, we reconstructed surface water hydrographs for all wetlands using the time-series of Landsat imagery from 1984 to 2011 (Section 4.3). Finally, we explored the dataset to determine if it could be used as a tool to classify wetlands by their hydrologic regime and monitor wetlands (Section 4.3). Figure 2 provides a flowchart of these steps.

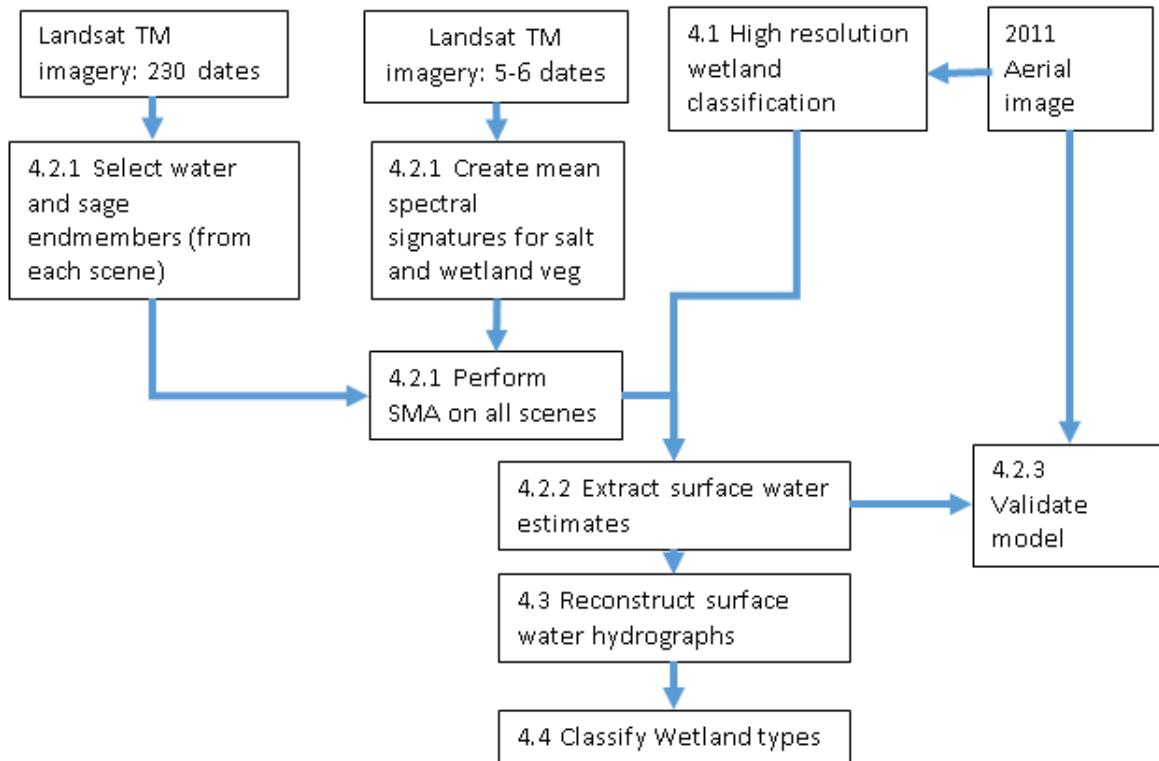


Figure 2: Flowchart of method steps

4.1 Data Pre-processing

We used a high-resolution wetland classification for Douglas County to summarize spectral mixture results for individual wetlands. The wetland classification was created using object-based image analysis of 2006 digital aerial images with 1-m pixel resolution, freely available through the United States Department of Agriculture, National Agriculture Inventory Program (NAIP). The classification was created through a rule based algorithm using wetland features, such as color, shape and texture determined from manual photo interpretation and is described in Halabisky, Moskal, & Hall (2011). The classification had an overall accuracy of 89% and a minimum mapping unit of 200 m².

We updated the wetland classification created from 2006 aerial imagery to classify wetlands that were dry or had been plowed since that time by adding the NAIP imagery from 2011 to the object based image analysis algorithm. In addition, we manually edited the updated classification to correct and remove misclassified wetland polygons (~ 40 hours). Most misclassification errors were due to small shadows, rock outcrops, or road sections that were dark in color and were spectrally similar to water. With the additional date of imagery our accuracy minimally improved by 1% to an overall accuracy of 90.3% ($\hat{k} = 0.85$) (Table 3). The confusion matrix was created using a stratified random sample of 177 points within the wetland classification and 100 additional points in the background matrix.

Table 3: Accuracy assessment for wetland classification with OBIA and NAIP imagery (overall accuracy = 90.3%, $\hat{k} = 0.85$) in Douglas County, WA, 2011.)

Classification Data	Reference Data			Total	User's Accuracy
	Open Water	Emergent Vegetation	Background		
Open Water	68			68	100.0%
Emergent Vegetation	4	82		86	95.3%
Background		23	100	123	81.3%
Total	72	105	100	277	
Producer's Accuracy	94.4%	78.1%	100.0%		
Overall Accuracy	90.3%				
\hat{k}	0.85				

All wetland components (i.e. emergent vegetation, open water) were merged to form wetland complexes. Wetland complexes that consisted only of wetland vegetation were not used for this analysis. From this classification, we selected wetlands larger than 600 m². We buffered complexes by 30 m to allow for small spatial shifts between Landsat image scenes.

4.2 Objective 1: Develop a method with minimal pre-processing to estimate surface-water extent for wetlands at scales below 30m.

4.2.1 Spectral mixture analysis

Spectral mixture analysis (SMA) is a method used to identify the fractional abundance of distinctive spectra, known as spectral endmembers, within the spectrum of a mixed pixel (Adams et al., 1986; Adams & Gillespie, 2006). Spectral endmembers represent samples of significant physical scene components and are selected from spectral measurements on the ground, spectral libraries (“reference” endmembers) or from the image itself (“image” endmembers). Samples measured on the ground generally are themselves mixtures and therefore do not yield “pure” spectral signatures of the material they represent. However, at image scales the spectral heterogeneity is commonly reduced and well-chosen spectra are sufficient for SMA (Adams & Gillespie, 2006). SMA has been shown to work well in water environments and in areas where there is high spectral contrast between classes (Shanmugam et al 2006).

Mathematically, SMA can be expressed as:

$$DN_i = \sum_j F_j DN_{i,j} + r_i \text{ and } \sum_j F_j = 1 \quad (1)$$

Where DN_i is the measured value of a mixed pixel in band i ; DN_j is the measured value of each endmember; F_j is the fraction of each endmember; r is the root mean square (rms) residual that accounts for the difference between the observed and modeled values (Adams & Gillespie, 2006).

We developed our SMA model using ENVI software version 4.8 (Exelis Visual Information Solutions, Boulder, Colorado). For every Landsat image we used all bands, except band 6, the thermal infrared band. The image endmembers were selected from areas mapped as water, sage steppe, salt, and wetland vegetation. Salt was chosen because many of the wetlands form a salt

crust when dry. Image endmembers for water and sage steppe were selected using specific geographic coordinates determined in the field based on our knowledge of the landscape and selected directly from each Landsat image (Figure 1). The benefits of selecting an endmember from the image is that atmospheric correction is not required as long as the geographic extent is not too broad to have significant variation in atmospheric effects (Aspinall et al 2002). The water endmember was selected from a deep portion of the Columbia River behind the Grand Coulee Dam (Figure 1). This part of the Columbia River has little to no flow and is low in suspended sediment therefore represents a reliable signature for water that remains stable throughout the year.

Spectrally pure pixels for salt and wetland vegetation are not apparent in every image. Therefore, we estimated image endmembers for salt and wetland vegetation using the mean spectral signature derived from an early summer and late summer image for three years: 1984, 1994, & 2004. Six images in total were used to calculate the mean endmember values for each of the six bands (29 Aug 1984, 28 Sep 1984, 24 Jul 1994, 26 Sep 1994, 30 May 1994, 30 Mar 2004, 21 Sep 2004) (Figure 1). The 29 Aug 1984 endmember for salt was omitted because there was not a spectrally “pure” pixel for that scene. Therefore, the salt endmember was sampled from five images instead of six.

We performed no atmospheric correction because we selected our water endmember directly from each image in the time series, minimizing error in the endmember fractions caused by atmosphere. However, because we used average spectra for two of our endmembers we cannot completely remove error from endmember fractions caused from changes in atmosphere between image dates. A sum-constrained linear spectral mixture model (for ENVI, an arbitrary but large sum constraint = 10,000 was specified, corresponding to the endmember fraction summing to ~1.00) was run on all scenes. Only the fractional abundances for water and the root mean square (rms) error were exported as a two-band image. Proportion of surface water generally ranged from <0 to 1.0, with some surface water values above 1.0. Any score below zero represents pixels with no surface water, while scores of 1.0 or above represent pixels composed entirely of surface water. We ran our SMA model on all 230 Landsat image scenes using batch processing

in ENVI IDL (Exelis Visual Information Solutions, Boulder, Colorado). Total processing time took roughly 4 hours.

4.2.2 Estimating surface water extent for wetlands

In order to estimate the surface water extent for wetlands we first converted all pixels from the SMA output to sub-pixel surface water area estimates (m^2). To do this we multiplied the fractional abundance of surface water for each pixel by the area of the pixel (i.e. $900 m^2$). This provided a sub-pixel surface water area estimate for each pixel in the image scene (Figure 3). Next, we summarized the sub-pixel surface water area estimates for each wetland using the buffered high-resolution wetland classification derived from 2006 and 2011 aerial imagery. The buffered wetland polygons were used to select (known as “extract by polygon” in ArcGIS) corresponding sub-pixel surface water area estimates which were summed for each wetland using python tools in ArcGIS 10.1 (ESRI, Redland, California). Mathematically this can be expressed as:

$$\sum_{i=1}^n F_i * a \quad (2)$$

Where F is the fractional abundance of water for pixel i ; a is the area of one Landsat pixel (i.e. $900 m^2$) and n is the number of pixels selected for each wetland polygon.

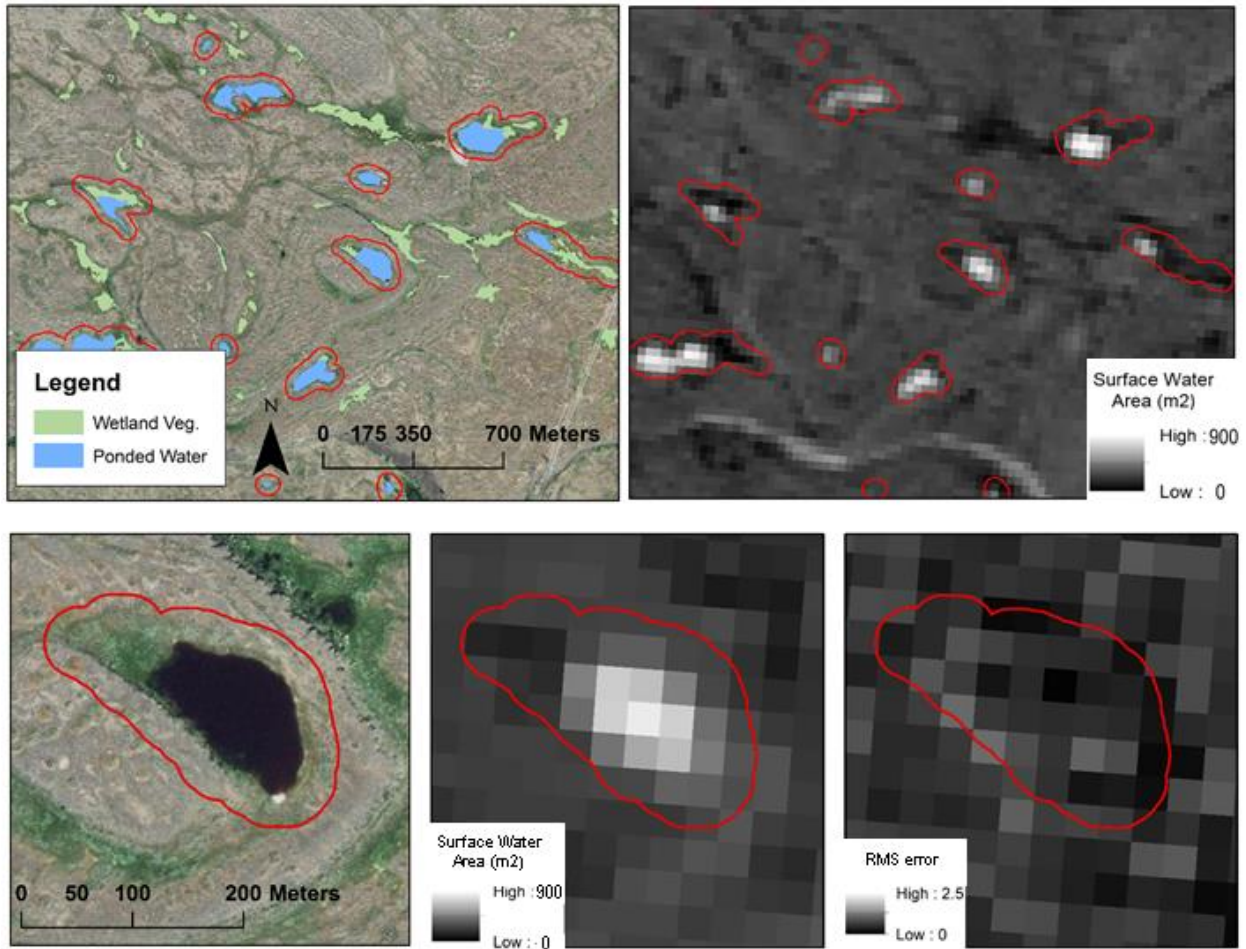


Figure 3: Example of combining high-resolution classification and sub-pixel surface water estimates from SMA. Wetland complexes, including pond and wetland vegetation (top left) were buffered by 30 m (red outlines). SMA results (top right) were summed for each wetland polygon to derive surface water extent. The example on the bottoms shows from left to right, a buffered wetland, the SMA results converted to surface water area, and rms error for one wetland, 3.4 hectares in size.

4.2.3 Validation

We used the 07 Jul 2011 Landsat image to validate our four-endmember SMA model. We compared SMA wetland surface water extent for this image to a reference dataset created through manual delineation of wetlands using high-resolution aerial imagery acquired at the same time (06 Jul 2011– 07 Jul 2011). To build our reference dataset, we used sampling with probability proportional to size to select 100 wetland polygons from our wetland classification.

We chose this sampling strategy for two reasons. First, we did not set a minimum mapping unit and wanted to see how error changed across multiple wetland sizes. Second, because wetlands <1 ha dominate the landscape an entirely randomly sample of wetland polygons would result in a sample primarily consisting of very small wetlands. The surface water extent of wetlands in the validation dataset ranged from 0 (completely dry) to 22.48 ha.

In order to understand error in terms of percent change we converted surface water area estimates into percentages by relativizing surface water area by the maximum inundation extent (derived from Landsat) for each wetland. We also relativized the reference dataset by the maximum inundation and compared it to the percent surface water from the SMA. We plotted the residuals from the relationship between percent actual surface water extent and percent modeled surface water extent against wetland size to see if error changed across wetland size. We assessed the rms output for the 07 Jul 2011 Landsat satellite image scene to determine that the four endmember SMA model accounted for all surface materials within each wetland polygon and calculated the percentage of pixels with a rms error above 2 DN. Additionally, we calculated the mean rms error for an area in the Columbia River that represented a homogenous body of water with the assumption that a model with acceptable levels of noise should have DN values below 2 (Nichol and Vohora 2004).

4.3 Objective 2: Reconstruct hydrographs

Surface water area estimates from all images (1984 - 2011) were exported for each wetland and used to reconstruct individual surface-water hydrographs using plotting tools in R statistical software (R Core Team, 2013).

4.3.1 Validation

No formal validation was performed on the reconstructed hydrographs, because we could find only one high-resolution aerial image acquired at the same time as a Landsat image. Instead, we visually compared hydrographs to annual precipitation patterns for the same time period (1984 – 2011). Monthly precipitation totals came from the PRISM Climate Group, Oregon State University, <http://prism.oregonstate.edu> (created 4 May 2015), which gathers climate observations from a wide range of monitoring networks and develops spatial climate datasets

covering the conterminous United States (Daly et al 2008). We plotted a moving average of annual precipitation using monthly precipitation totals as taken from PRISM data along with our reconstructed hydrograph to visually assess if wetland surface water area generally tracked changes in precipitation.

4.4 Objective 3: Use hydrographs to classify wetland types and monitor wetland change over time

The methods above enabled us to reconstruct wetland hydrographs. We then explored these reconstructed hydrographs to determine if the dataset could be used as a tool to classify and monitor wetlands. We classified wetlands in two ways. First, we categorized wetlands based on the percentage of years a wetland dried out. We considered a wetland dry when surface water extent fell below a threshold of 25% as not all years captured the exact date of 100% drying. Because the wetlands in Douglas County are shallow, depressionals wetlands when the surface area of water in a wetland falls below 25%, the water depth is very shallow and the wetland is near drying. Next, we classified wetlands by hydroperiod type based on the seasonal patterns of an average year of precipitation (2011) using wetland hydrologic modifiers from the Cowardin classification scheme; temporarily flooded, seasonally flooded, and permanently flooded (Cowardin et al 1979). Temporarily flooded wetlands only hold water for brief periods in the growing season. Seasonally flooded wetlands hold water for extended periods in the growing season, but are usually completely dry by early summer. A permanently flooded wetland shows little change in surface water area throughout the summer months.

In order to determine if hydrographs could be used to monitor wetland change we selected all wetlands with maximum surface water extent above 1 ha as patterns are more distinct at this scale to create a subset of 481 wetland hydrographs. We next, organized hydrographs with similar patterns into unique groups. We looked at historic imagery of a sample of wetlands from each group to determine if we could distinguish the cause of the hydrograph pattern.

5 Results

5.1 Objective 1: Develop a method with minimal pre-processing to estimate surface-water extent for wetlands at scales below 30m

Our method captured the surface water extent for each wetland within our wetland classification for our 07 Jul 2011 Landsat image. The rms image had no distinct pattern within the wetland boundaries (Figure 3), indicating that the SMA technique accounted for all significant endmembers. Because the objective was to estimate surface water extent, we were not concerned about error rates outside of the delineated wetland basins. Twenty percent of pixels within the wetland classification had an rms error above 2 DN. Sampling of pixels behind Grand Coulee Dam on the Columbia River, a homogenous waterbody, had a low rms error. Mean rms error was 0.45 DN with all rms error for the Columbia River falling within a range of image noise between 0.06 and 1.14 DN.

Comparisons of the SMA wetland surface water estimates to the validation dataset show a R^2 value of 0.99 ($p < 0.001$) (Figure 4) and a standard error of 0.85. Percent surface water estimates, as expected, had a lower correlation, with a R^2 value 0.85 ($p < 0.001$) (Figure 4) and a standard error of 0.08. Although, still low, further examination of the residuals compared to the size of the wetlands shows a larger magnitude of error for smaller wetlands (Figure 5)

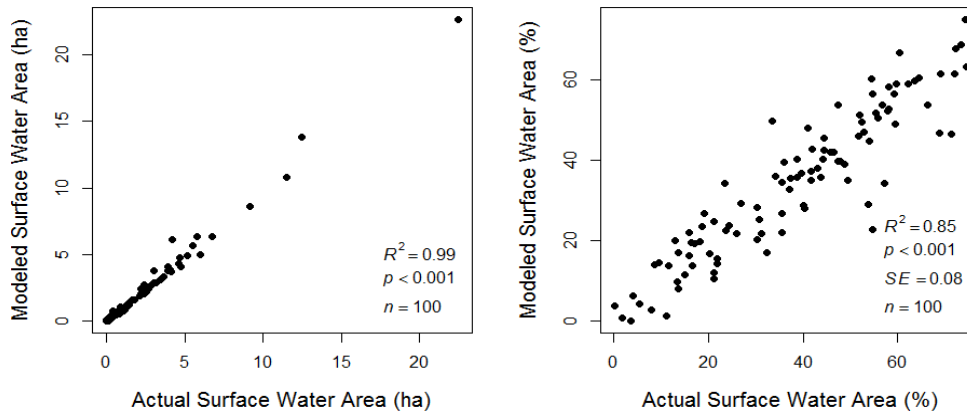


Figure 4: Figure on left shows the comparison of modeled surface water area as derived from SMA method against actual surface water area derived from manual delineation of aerial photos. Figure on right shows the percent of modeled surface water extent compared to the percent of the

actual surface water extent. Percent surface water extent was derived by relativizing wetland surface water area by the maximum flooded area derived from SMA time series.

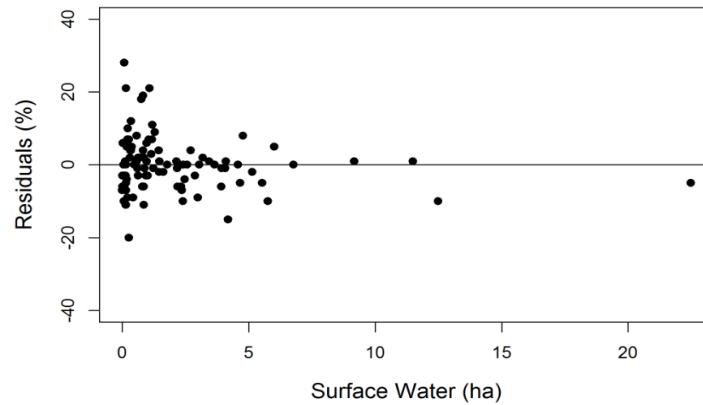


Figure 5: Residuals of relationship between percent predicted surface-water extent to percent actual surface water extent. Surface water extent as measured by the validation dataset is plotted on the x-axis.

5.2 Objective 2: Reconstruct individual wetland hydrographs from 1984 to 2011

Our technique produced detailed hydrographs for 750 wetlands spanning a time period from 1984 to 2011, across Douglas County. The individual hydrographs capture both long-term change and seasonal change to surface water extent within wetlands and appear to follow changes in precipitation levels (Figure 6). As described above smaller wetlands had higher error. An example of a small wetland hydrograph is shown in Figure 7. This wetland has a maximum size of 1530 m². The validation dataset estimated the surface water extent for this wetland (derived from the 2011 aerial image) to be only 800 m² in size, less than one Landsat pixel. The SMA technique estimated the wetland to be 140 m². Of all the wetlands in the validation dataset it has the highest residual (28%). Despite this error it is clear that this wetland only fills up during wet years (mid 1980s, mid 1990s, and a few years in the 2000s), when precipitation levels are above average.

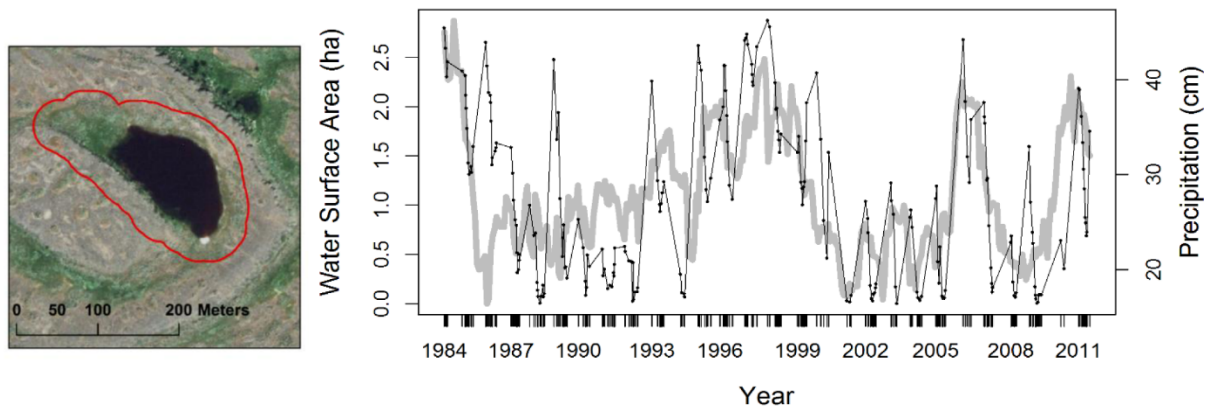


Figure 6: Example of a hydrograph spanning 1984 - 2011. This figure represents the hydrograph of the wetland highlighted in Figure 3, which is 3.4 ha in size. X-axis tick marks represent number of observations. Reconstructed hydrograph measures both inter- and intra- annual change. A moving average of annual precipitation calculated from monthly totals is shown in grey. The hydrograph of this wetland appears to follow changes in precipitation levels.

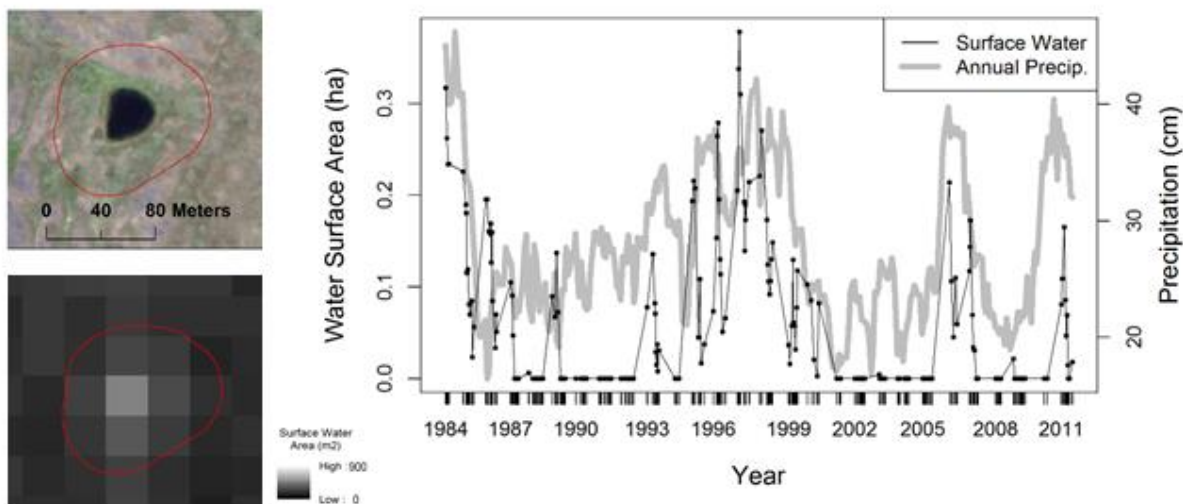


Figure 7: Example of a hydrograph for a small wetland. This wetland had a maximum size of 1530 m². The surface area of the validation dataset (derived from 2011 aerial image) estimated the surface area to be only 845 m² in size (less than one Landsat pixel).

5.3 Objective 3: Use hydrographs to classify wetland types and monitor wetland change over time

Reconstructed hydrographs show seasonal change and can be used for classification of wetland by hydroperiod type. Figure 8 shows the hydrograph for three different wetland hydroperiod types based on both long-term and seasonal patterns found within the dataset. Note, that although the three wetlands (Figure 8 a, b &c) are different sizes, they are distinguished by their hydrologic regime not their size.

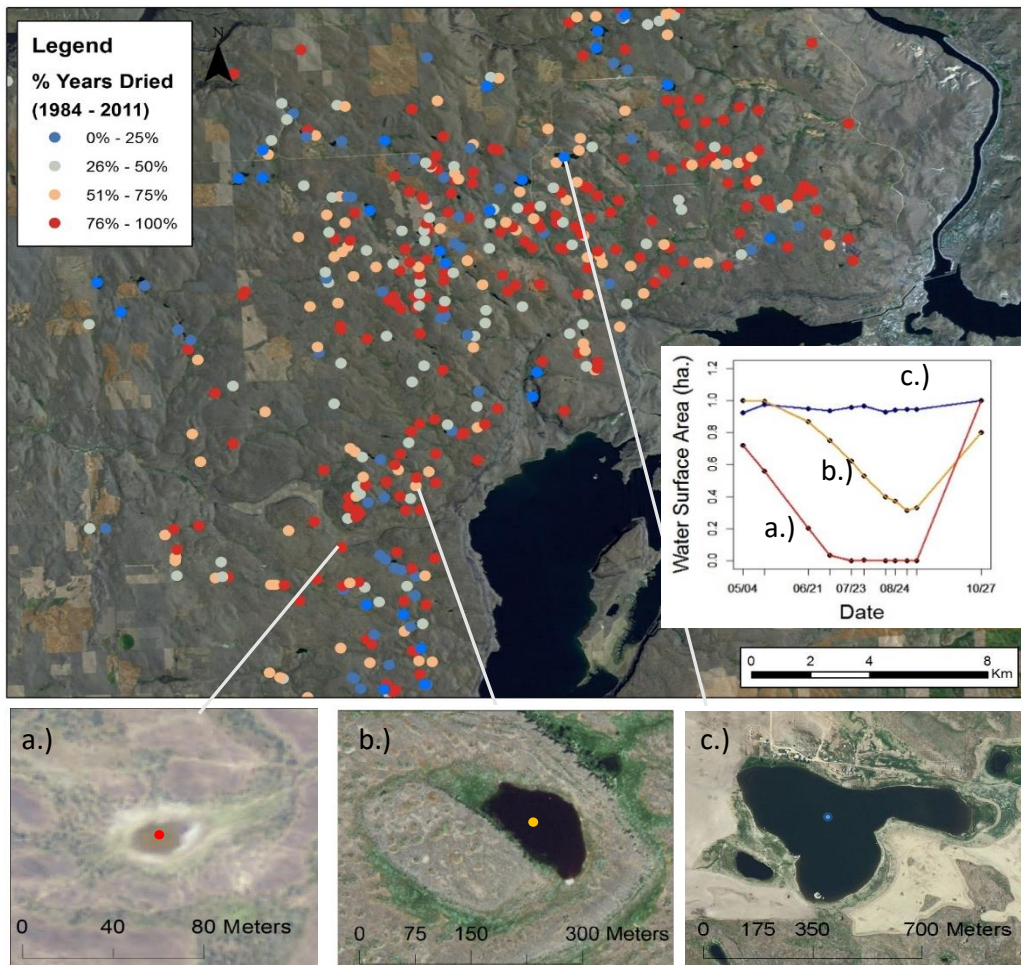


Figure 8: Example of a hydrograph for three different wetland types for the year 2011; temporarily flooded wetland (a.), seasonally flooded wetland (b.), and a permanently flooded wetland (c.). The map shows the spatial variability of wetland types in northeast Douglas County based on the number of years the wetland fell below 25% water surface area between 1984 and 2011.

A temporarily flooded wetland (Figure 8a) dries up early in the summer season in an average year of precipitation and dries up most years. A seasonally flooded wetland (Figure 8b) dries up between 51 to 75% of the years that we measured. In an average year of precipitation it significantly declines in surface area, but does not completely dry up. A permanently flooded wetland (Figure 8c) does not dry up and has little seasonal change to surface water extent.

We detected five different patterns of wetland hydrographs. The first group (318 wetlands), appeared to follow precipitation patterns similar to the patterns evident in Figures 6-8. The second group of hydrographs (42 wetlands) did not track precipitation levels and had an irregular zigzag pattern (Figure 9). These hydrographs represent misclassification error carried over from the wetland classification. This hydroperiod pattern is likely due to shadows that were misclassified as open water wetlands in the wetland classification. The hydrograph for the misclassified shadow appears to increase in surface water extent during summer for three years (1984, 1993, 2011), which is likely driven by seasonal changes in the cast shadow as there is no wetland evident in the aerial photo.

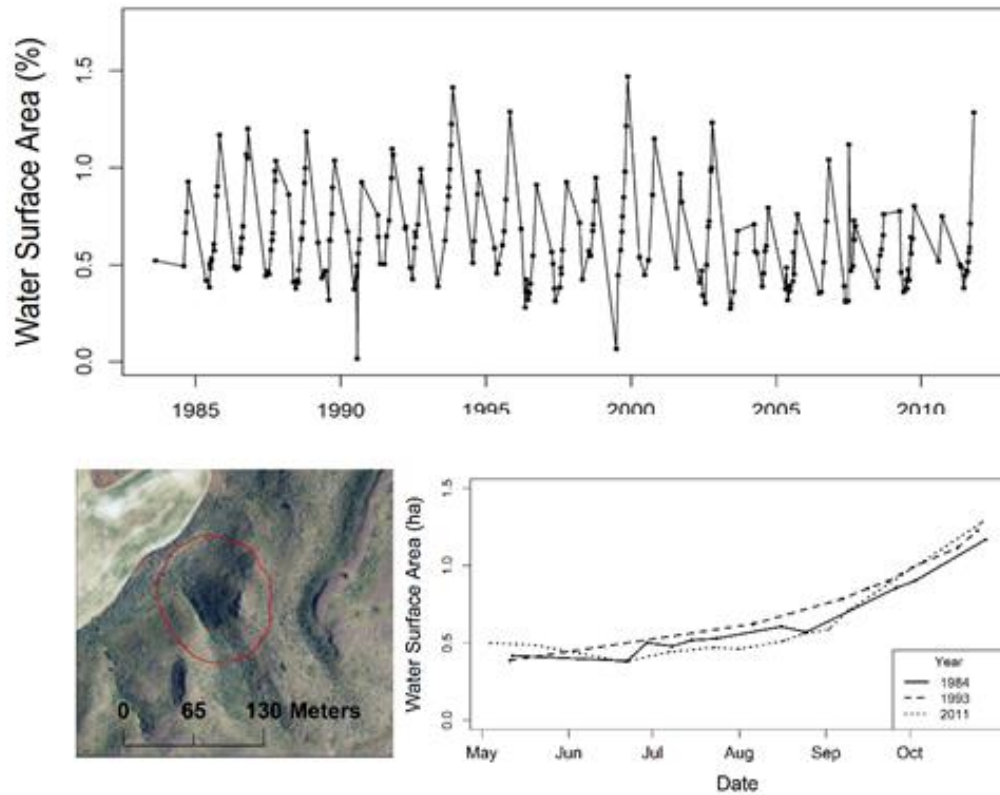


Figure 9: Example of a ‘hydrograph’ of a shadow that was misclassified as a wetland. The long-term hydrograph (top) has a zig zag pattern that does not follow precipitation patterns. The lower right hand graph shows the seasonal hydrograph for three years (1984, 1993, & 2011). Surface water extent increases through the summer season, contrasted with a typical wetland which dries out as the summer temperatures increase and precipitation levels typically decrease.

The remaining wetland hydrographs diverged from long-term precipitation patterns (Figure 10), but did not have the same regular zigzag pattern as those in the second group. The third group (84 wetlands) showed an obvious decrease in surface water extent over time. Figure 10 (top) provides an example of a wetland that is drying out over time and is now has only 50% of the total surface water extent it had in the mid-1980s. The fourth group (32 wetlands) show irregular patterns of flooding and drying. Figure 10 (middle) is an example of a wetland that is repeatedly plowed over for farming. The fifth group (5 wetlands) is rare on this landscape, but shows an increase in long-term surface water extent. Figure 10 (bottom) shows a hydrograph of a wetland that was created through hydrologic engineering.

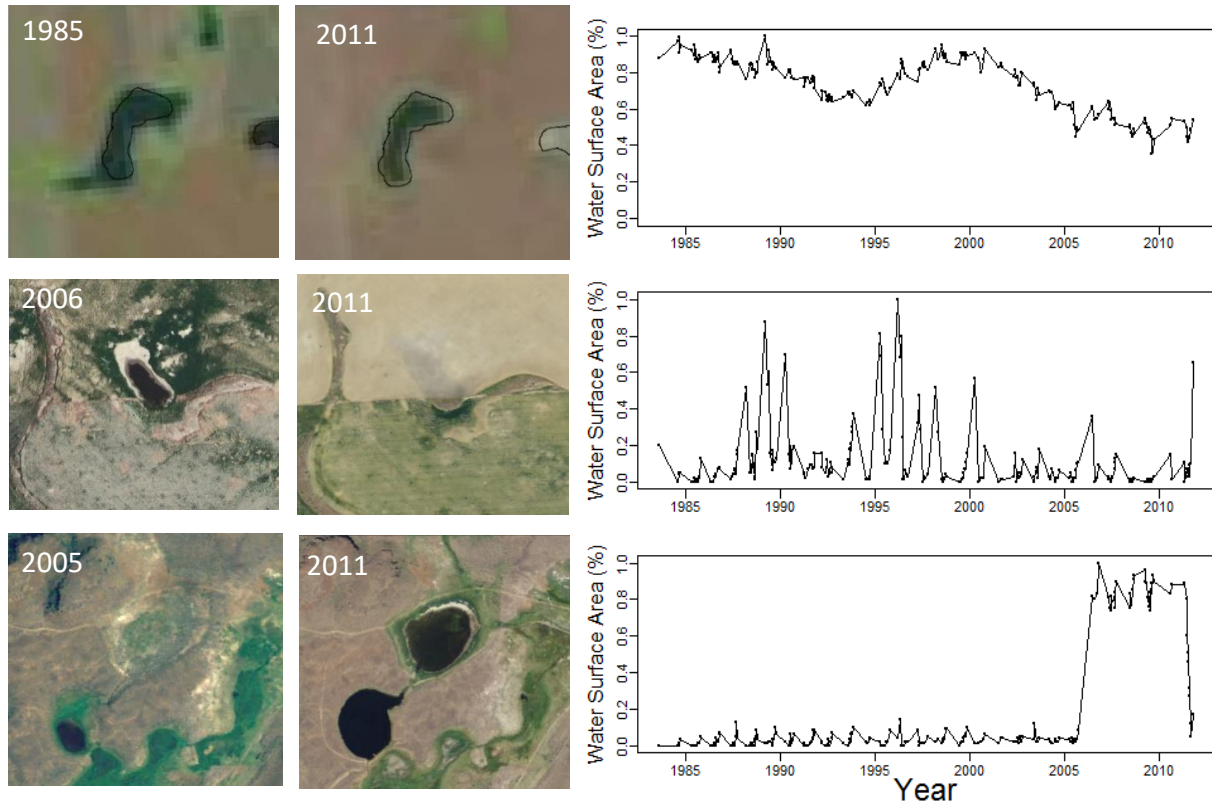


Figure 10: Example of hydrographs for three wetlands undergoing abnormal change; shrinking wetland (top), plowed wetland (middle), and created wetland (bottom).

6 Discussion

Our method provided detailed hydrological data for all surface water wetlands within our 4,714 km² study area of Douglas County, WA, USA with minimal data pre-processing. The individual hydrographs capture both long-term and seasonal change to surface water extent of wetlands. To the best of our knowledge, this is the first such reconstruction of wetland hydrographs for all wetlands across a broad landscape at such a fine spatial and temporal resolution. As such, it offers novel insight into landscape-level wetland dynamics, reconstructs data for testing hydrologic or ecological hypotheses, and provides a useful tool for hydrological monitoring of wetlands at multiple scales; from large landscape analysis to individual wetland monitoring in high contrast semi-arid locations in the western United States.

6.1 Sources of error

Spectral mixture analysis yields spectral abundance of the spectral endmembers in the mixed pixel spectrum. It is related to the physical abundance of the corresponding physical endmember, but is not necessarily a one-to-one ratio. A likely source of error is due to a mismatch between the image endmember chosen in our SMA model, which came from deep water, and water contained in wetlands. The spectral endmember we chose for water was likely closely matched to the physical endmember we modeled except where algae, floating vegetation, and areas of shallow water, occurred in wetlands. Wetlands containing wet mud may look partially filled with water because of spectral mixing between water and mud. In addition, we cannot completely remove atmospheric error from endmember fractions because we used average spectra for two of our endmembers.

As indicated in Figure 5, error was greatest for small wetlands. Smaller wetlands are composed of fewer Landsat pixels and more likely to be composed of mixed pixels. Because our model used average spectra for two of endmembers (i.e. salt and wetland vegetation) we assume that error will be greatest for small wetlands which are composed of mixed pixels that contain proportions of these two endmembers. Although the accuracy decreased for smaller wetlands, it still provides useful information on their hydrology and could be used even on wetlands smaller than two Landsat pixels (1800 m²) for monitoring of large disturbance to wetland hydrology (e.g. land conversion). Despite higher levels of error, this method still provides useful information on the hydrology of very small wetlands (Figure 7).

Our validation method does not assess error outside of our wetland classification. Therefore, it is important to use a wetland classification that accurately delineates wetlands and has both low errors of commission and low errors of omission. Although a high-resolution wetland inventory exists for our study area (i.e. the US National Wetland Inventory), it did not meet this criteria. Ideally, we would have preferred a classification derived from historical aerial imagery acquired prior to 1984 so that we could capture wetlands that had been filled or drained before 2006, the date of imagery that our classification is based on.

6.2 Method strengths and limitations

Rather than tracking surface water extent of individual pixels through time or summarizing changes to surface water at the landscape scale as in previous approaches, our method reconstructs hydrographs specifically for individual wetlands. Because of this, our SMA model measures surface water extent in terms of area, providing an intuitive dataset. By contrast, it can be difficult to understand how other sub-pixel methods based on remote-sensing indices or changes in band reflectance (e.g. Landsat TM 5 Band 5) translate to on-the-ground conditions without field calibration. However, our method measures surface water extent, not water depth which is of great utility in wetland science. Additional research would be necessary to determine if surface water area could be converted into water depth or water volume. The addition of a high resolution digital terrain models derived from infrared lidar flown when wetlands are dry or the use of green lidar to map wetland bathymetry may prove fruitful (Allouis et al 2010; Lane and D'Amico 2010; Richardson and Moskal 2014).

Because our method incorporates a high-resolution wetland delineation it works best for discrete wetlands that can be delineated into polygons. For extensive and complex wetlands it may not be useful to track surface water extent of the entire wetland. In these instances it could be more useful to track individual pixels through time using other methods such as those outlined by Gomez et al. (2010).

An additional limitation is that accurate wetland classifications are not available in many areas. However, it is important to note that in some instances manual delineation of wetlands may provide an adequate alternative to remotely sensed classifications. Furthermore, our method can be used as a tool to automate removal of erroneously classified shadows from a dataset because as demonstrated in figure 9 shadows have a unique temporal signature.

Areas with limited high-quality cloud-free Landsat imagery may not benefit from this method because the imagery may be too infrequent to reconstruct meaningful hydrographs. Additionally, wetlands with short hydroperiods may not be captured at the interval of Landsat imagery (i.e. 16 days). In these instances, other methods that used multiple Landsat images to

predict the hydrologic regime of wetlands (Beeri and Phillips 2007; Reschke and Hüttich 2014) may be more appropriate.

Our method requires selecting an image endmember from deep, sediment free water within the image scene. Accuracy would be impacted if the image endmember was not sampled from a spectrally pure water sample or included seasonal changes in water clarity either in the image endmember or in the wetlands themselves. This requirement cannot be met in many landscapes. Douglas County has few trees, subtle topography, and therefore few resolved shadows. Further testing across more diverse and complex landscapes is necessary to determine applicability of our method in non-arid landscapes. As shadows and water have similar spectral signatures, this method would not work well in areas where shadows mixed with wetland area, such as forested wetlands or areas with steep topography. Without significant modification this method would not work on wetlands with little or no surface water, such as wet meadows.

6.3 Potential Applications

Unlike rivers and streams, which are typically monitored in greater numbers and at higher frequencies, hydrologic data for wetlands is unavailable for the vast majority of regions. This limitation has inhibited exploration of questions related to wetland hydrology and advancement of basic scientific understanding of wetland dynamics for some time (Mitsch and Gosselink 2007). Our method opens a new area of wetland science by potentially providing rich hydrologic data for a large number of wetlands over a broad landscape.

By providing a large sample size of wetland data covering a broad area, our method facilitates myriad explorations including characterizing wetlands and classifying wetland habitat types (Snodgrass, Komoroski, Bryan, & Burger, 2000), understanding environmental variability (LaBaugh et al 1998), evaluating the relationships between wetland dynamics and climate variables (Winter 2000), calibrating hydrologic models of climate impacts (Lee et al 2015), quantifying ecosystem services (Woodward and Wui 2001), and elucidating the role of groundwater or other hydrologic inputs. When coupled with biological data, these data support novel ecological investigations that have been hindered by the lack of time series data for wetlands. Opportunities include basic research on the relationship between hydrologic variation

and species occupancy, composition, and richness (Tavernini et al 2005); population or community dynamics and species diversity maintenance (Tuljapurka 1990; Chesson 2000; Boyce et al 2006; Morris et al 2008); metapopulation and metacommunity dynamics (Hanski and Gaggiotti 2004; Leibold et al 2004) and ecosystem services (Brauman et al 2007). Reconstructed hydrologic data also greatly enhance capacity for applied research on endangered species or critical ecosystem responses to hydrologic variation. For example, time-series data can be used to establish baselines and evaluate trajectories of change and risk associated with shifts in land use and climate change. Comparing hydrographs with precipitation or land use change data via formal time series analysis would be another fruitful avenue that may elucidate causes of hydrologic variability in wetlands.

Additionally, our method can be used as a monitoring tool by identifying abnormal changes to wetland hydrology (Kentula 2007) and assessment of regional trends over time, including shifts in the relative coverage of different wetland types and changes in wetland function critical to understanding the full picture of wetland dynamics beyond direct land conversion.

7 Conclusion

We demonstrated a reliable and cost-effective method for wetland assessment that provides information on status and trends of surface water for individual wetlands in semi-arid regions. Our approach using high-resolution wetland delineations and spectral mixture analysis of Landsat imagery substantially increases the available hydrologic data for wetlands by reconstructing detailed wetland hydrographs without the need for extensive pre-processing. These methods allow for new insights into landscape level changes to wetland hydrology and conservation actions. Further research is needed to test limitations in other non-arid regions.

8 Acknowledgments

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Chapter 2. Exploring the temporal dimension in object based image analysis to improve remotely sensed observations of wetlands

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Abstract

Research on object-based image analysis has typically focused on the spectral and spatial domains to identify and classify objects, but the temporal domain is far less explored. For some objects, which are spectrally similar to other landscape features, their temporal pattern may be their sole defining characteristic. When the temporal domain is used it is often constrained to a specific number of images and selected because they cover the perceived range of temporal variability of the features of interest. Here, we provide a straightforward way to identify wetlands using a time series of Landsat imagery by building a Random Forest model using each image observation as a variable in our model. Our approach is easy to implement and classified wetlands with a high level of accuracy, even small ephemeral wetlands composed of only a few Landsat pixels. We explored how sampling design (i.e. random, stratified, purposive) and temporal resolution (i.e. number of image observations) affected classification accuracy. We found that sampling design introduced bias in different ways, but did not have a substantial impact on overall accuracy. We also found that a higher number of image observations up to a point improved classification accuracy dependent on the selection of images used in the model. While time series analysis has been part of pixel-based remote sensing for many decades, with improved computer processing and increased availability of time series datasets (e.g. Landsat archive) it is now much easier to incorporate time series into object based image analysis classification.

1 Introduction

Object based image analysis (OBIA) is a remote sensing technique used to identify and classify objects through a process of pattern recognition (Blaschke et al., 2014). OBIA differs from pixel-based techniques by aggregating raster pixels with similar characteristics into segments or objects (Blaschke, 2010). Once an image raster is segmented, the objects can be classified using analyst-defined rules, machine learning techniques, or statistical methods. Because the object no longer consists of a single pixel, additional features such as shape, size, and context, not just the spectral features, can be used to drive the classification. Object based approaches are commonly used on high spatial resolution data with limited spectral bands (e.g. red, blue, green) where traditional pixel-based approaches are less effective (Strobl and Blaschke 2001). Often, additional raster or vector layers, such as road layers, slope indices, and soil data, are added to provide additional variables to help characterize objects. For a good review of OBIA, see (Blaschke, 2010).

OBIA is typically applied in instances where image features are composed of more than one pixel and grouping of these pixels into segments provides additional characteristics of that landscape feature (e.g. object size) that are not available at the single pixel scale (Blaschke et al 2014). For this reason, OBIA is most often used on high spatial resolution imagery where heterogeneous landscape features can be resolved (Blaschke 2010). Because of the dependence on higher spatial resolution imagery, which are not typically acquired at frequent intervals, OBIA classifications have primarily relied on spectral, spatial, and contextual characteristics to distinguish objects, and have focused less on temporal patterns. When the temporal dimension is used to characterize an object rarely is the entire time series used, relying instead on a selection of image observations that capture the assumed temporal variability of the landscape feature of interest (Löv et al 2015; Gabrielsen et al 2016; Gil-Yepes et al 2016).

Classification based on a time series of imagery is more commonly used in pixel-based approaches (Beeri and Phillips, 2007; Collins et al., 2014; Gómez-Rodríguez et al., 2010; Ozesmi and Bauer, 2002; Reschke and Hüttich, 2014). However, pixel-based approaches cannot incorporate the spatiotemporal patterns of the objects themselves that can only be captured at the object level. For many landscape features, such as wetlands, meadows, and agricultural fields,

temporal variability may be the key determinant of class membership (Townsend and Walsh 2001; Gil-Yepes et al 2016). These temporal patterns may only be detected once pixels are grouped together into objects. For some objects the temporal patterns may differ for pixels near the center of the object compared to pixels near the edges of objects. In the example of wetlands, pixels in the center of the wetland object may be permanently flooded while pixels near the edge may be seasonally flooded, but the temporal pattern of the entire object is what distinguishes it from other landscape features.

1.1 Data resolution

There has been a consistent push from the conservation community to acquire data at higher resolutions in order to detect finer scale patterns of landscape features. While the term resolution is most commonly used to refer to the spatial resolution of an image, there are in fact four resolution domains; spatial, temporal, spectral, and radiometric (**Figure 1**). Radiometric resolution is defined as the smallest difference in exposure that can be detected in an image. While radiometric resolution can be helpful it is to a much lesser degree than the three other resolution domains further discussed here.

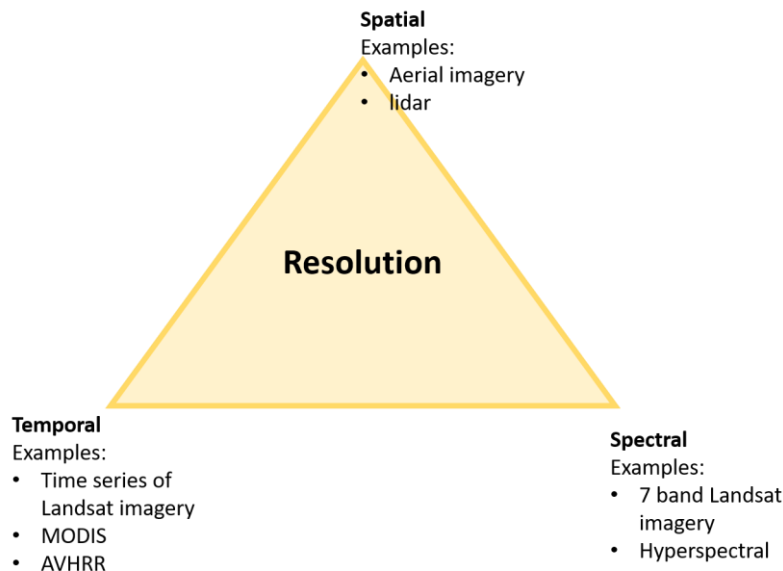


Figure 1. Examples of the data types for each of the three resolution domains; spectral, spatial, and temporal.

The term resolution existed in the field of photogrammetry long before the advent of pixels and was originally defined as the scale at which the object of interest could be resolved. It is only in the digital age that the term resolution has come to be defined in terms of image attributes of the sensor (e.g. pixel size, frequency intervals, number of locations along the electromagnetic spectrum). Therefore, the terms “high”, “moderate”, and “low” resolution are both subjective and relative to the remote sensing analyst. In general, however, “high” resolution data refers to pixel finer pixels resolutions, more frequent observation intervals, and higher number of image bands. Currently, there is no single sensor that provides data at the highest spatial, temporal, and spectral resolutions available. Instead each sensor is optimized for a particular task and there are tradeoffs in resolution domains.

Blaschke et al. (2010), offers a thoughtful discussion on high spatial resolution data and how pixel-based approaches are insufficient at this scale. However, the same arguments laid out by Blaschke et al. (2010) can be extended to the other two domains – spectral and temporal – even if the object cannot be resolved spatially. High spatial resolution imagery may not be required to identify pixels with strong temporal patterns.

1.2 Object based image analysis of wetlands

Wetlands represent many diverse and distinctive ecosystems united by the common fact that their dynamics are fundamentally driven by fluctuating availability of water. The hydroperiod, defined as the timing and duration of flooding, is the most important determinant in the establishment and maintenance of specific wetland habitat types and the services that they provide (Babbitt, 2005; F J Correa-Araneda et al., 2012; Mitsch and Gosselink, 2007; Tavernini et al., 2005). Wetland plants and animals are specifically adapted to the hydroperiod having developed mechanisms to deal with the timing and duration of flooding within a wetland (F.J. Correa-Araneda et al., 2012; Snodgrass et al., 2000).

Wetlands provide a good example for explorations of the temporal dimension as the time varying nature of the hydrologic inflows and outflows of wetland makes them temporally dynamic. Wetlands are also spectrally similar to other objects in the landscape. A flooded wetland may resemble shadows from trees or topography. A dry wetland may be spectrally similar to an

agricultural field or grassland. Therefore, OBIA of wetlands using high spatial resolution imagery (<30m) often relies on other object features (e.g. shape, texture) or additional data layers such as lidar derivatives (e.g. topographic wetness indices), soils data, and radar (Halabisky et al 2011; Halabisky, Hannam, Long, Vondraseck, Moskal 2013; Kloiber et al 2015). However, in some regions high spatial resolution imagery (<30m) or ancillary data is not available. Additionally, remote sensing using high spatial resolution dataset can be computationally prohibitive when scaled to large extents.

Previous researchers have employed multiple dates of imagery to map wetlands. Frohn et al.(2009) used OBIA of two Landsat images, an early summer image and a late summer image to identify isolated wetlands. Murphy et al. (2016) used nine dates of Landsat imagery from a wet year, a dry year, an average year of precipitation to classify wetland pixels along a gradient of ephemerality. Halabisky et al. (2016) used OBIA of two dates of aerial imagery to reduce errors of omission of semi-arid wetlands that were dry or plowed in one of the aerial images. What is lacking from these analyses is exploration of OBIA classification using the entire time series of data.

1.2 Research Questions

Our aim for this research was to explore how temporal characteristics can be used to classify objects when distinguishing spectral, spatial (e.g. shape) or other characteristics are limited. To do this we used a Random Forest model to identify wetlands using a time series of 285 Landsat satellite images (1984 – 2011) as input variables into our model. In addition to testing the accuracy our approach, we explored the following questions:

- 1.) what is the best sampling design for collecting training data to be used in Random Forest classification of wetland objects; and
- 2.) how does temporal richness (number of satellite observations) impact classification accuracy?

In addition to examining the accuracy of our proposed approach, we sought insight concerning the effect of (1) sampling design for the collection of training data; and (2) the number and

arrangement of available images on classification accuracy.

2 Methods

2.1 Study Area

We selected Douglas County, Washington in the northwest of the United States for our study area as it contained wetlands with variable hydrologic patterns of flooding and drying and a high number of spectrally similar objects (**Figure 2**). Douglas County is a semi-arid landscape that is 4,714 km² in size. Most wetlands in our study area are isolated, depressional wetlands. While there is considerable variability in the hydrologic regime they all follow a similar annual flooding and drying pattern, filling up in the winter months and drawing down in the hotter, drier summer months. Spectrally similar objects that occur throughout the landscape include, but are not limited to, shadows from topography, tree canopy, and human built structures. Rock outcrops and small mining operations occur in locations within Douglas County and their dark features mimic the spectral signature of surface water flooding. Thus this case study is a good test of methods that seek to avoid such problems via temporal analysis. Ranching and farming are dominant land uses, and several urban areas, are also present in the geographic domain. In addition to climate and geologic characteristics, these human land uses may have impacts on the hydrologic regime of wetlands.



Figure 2. Study area. Columbia Plateau ecoregion. Black wireframes represent the two Landsat satellite scenes used in this study.

2.2 Materials

2.2.1 Input Data

We downloaded 285 Landsat Thematic Mapper 4 and 5 satellite images from two Landsat scenes (Path 45, Row 27 and Path 45, Row 26) acquired between 1985 and 2010 from the United States Geologic Survey (USGS) GLOVIS website (<http://glovis.usgs.gov/>) (**Table 1**). We only downloaded images acquired between March and October as wetlands in the winter months are typically frozen. We masked out all clouds and cloud shadows from the Landsat satellite imagery using the cloud mask provided by the USGS (<https://landsat.usgs.gov/espa>). We also used three additional ancillary datasets; a vector dataset of roadlines from the Washington State Department of Transportation, a slope index calculated from a 10m USGS digital elevation model, and a raster dataset of irrigated crop locations from the Washington State Department of Agriculture (Table 1). We buffered road lines by 30 meters to capture the width of the road.

Table 1. Materials

Datasets	Data Type	Source
Landsat TM 4 & 5	Raster	United States Geological Survey
Roads	Vector	WA Dept. of Transportation
Slope Index	Raster	Derived from USGS 30m Digital Elevation Model
Irrigated Crops	Raster	WA state Dept. of Agriculture
Wetland Classification	Vector	Derived from OBIA of 1-meter resolution aerial imagery (Halabisky et al. 2011, Halabisky et al. 2016)

2.2.2 Training and validation data

We used a pre-existing wetland classification dataset for Douglas County to train and validate our Random Forest model. The wetland classification was created using OBIA of 2006 and 2011 aerial images with 1m pixel resolution, freely available through the United States Department of Agriculture, National Agriculture Imagery Program (NAIP). The classification was created through a user defined rule-based algorithm using wetland features, such as color, shape and texture determined from manual photo interpretation and is described in Halabisky, Moskal, & Hall (2011) and Halabisky et al. (2016). Overall accuracy of the wetland classification was 90.3%.

2.3 Developing percent surface water images

As a first step in our process, we converted the time series of Landsat imagery into sub-pixel estimates of surface water area using a constrained four-endmember spectral mixture analysis (SMA) model as outlined in Halabisky et al. (2016). Briefly, SMA uses the spectral signature of materials (called endmembers) found within the image scene to estimate the proportion of materials within the spectrum of a mixed Landsat pixel (Adams et al., 1986; Adams & Gillespie, 2006). Two endmembers (water, sagebrush) were taken directly from each scene, while two endmembers (salt, wetland vegetation) were derived from six Landsat dates as spectrally “pure”

pixels are not available for every image. This technique provided a fractional estimate of surface water for each pixel ranging from 0 to 1 for each image in the Landsat time series.

2.4 Delineating wetlands using OBIA

We used OBIA to identify and delineate potential wetland objects using the time series of sub-pixel surface water area estimates. OBIA was performed using eCognition Developer 9.0. Because wetlands in our study area typically flood in the spring, but may dry up in the summer, we calculated the spring (March 1 – June 1) mean surface water extent for each pixel for three decades; the 1980s, the 1990s, and the 2000s. As a first step, we ran a segmentation on the three spring raster images and the slope index (scale parameter = 2), which created very small objects, 2 -3 Landsat pixels (30 m²) in size. The scale parameter affects the size of the segmented objects and is related to the spatial resolution of the data inputs. We chose a scale parameter of 2 based on visual assessment of the segmentation output. Next, we masked out roads, steep areas (slope index > 5 degrees), and irrigated crops in order to limit the number of false positives. Smaller roads, driveways, and areas where road lines did not match could not be masked out. Because the slope index was derived from a 10 m digital elevation model it was only useful at masking out large shadows created by steep topography.

Finally, we classified wetland objects that on average had 40% or greater estimates of surface water area from April 1 – June 1 in the 1980s, the 1990s, or the 2000s as *potential wetland* objects. We chose this threshold through visual assessment with the goal of identifying all areas that held water in the spring, while limiting errors of commission. The SMA method detected low levels of surface water in highly disturbed areas, such as plowed fields. A threshold below 40% incorrectly mapped upland areas as wetlands, increasing errors of commission. In addition, we wanted to limit analysis of wetland fluctuations to the primary basin and did not want to include areas that had overbank flooding as this produced hydrographs that overestimated the size of the wetland. We exported the results as a Geographic Information System (GIS) shapefile.

Following methods outlined in Halabisky et al. (2016), we buffered the output GIS shapefile by 30m to address issues of imperfect alignment between satellite images. The buffered polygons

were used to select (known as “extract by polygon” in ArcGIS) corresponding sub-pixel surface water area estimates from the Landsat time series which were summed for each wetland using python tools in ArcGIS 10.1 (ESRI, Redland, California). This process created a unique time series of surface water area estimates spanning from 1984 – 2011 for each polygon. We realized that in using a low threshold (40% percent surface water area for each wetland object) for classification that many of the polygons represented false positives.

2.5 Identifying wetlands using the temporal pattern of flooding and drying

We used a Random Forest classifier to identify wetlands based on their temporal pattern. Random Forest is a nonparametric, bootstrapped, decision tree method (Breiman, 2001). We used the R package randomForest for our modeling (Liaw and Wiener, 2002).

The time series for the *potential wetland* objects we created was irregular because the two Landsat images scenes have different acquisition schedules. Additionally, many observations are missing due to areas that we masked out using the USGS cloud mask. Random Forest does not allow for missing data. In order to resolve missing data, we fit a spline to all missing values using a cubic spline interpolation in the R statistical package. Finally, we converted surface water area estimates into percent surface water by normalizing each wetland by its maximum surface water area (m²) derived from the time series.

2.5.1 Training and Validation

In order to train and validate our Random Forest model we overlapped potential wetland polygons derived from the Landsat time series with our high-resolution wetland classification. Potential wetlands that overlapped with our high-resolution classification were deemed wetlands, ones that did not overlap were labeled as non-wetlands. Some wetlands were not present in the 2006 and 2011 aerial imagery, which the high resolution classification was based, due to the ephemeral nature of wetlands or because of human caused draining or disturbance. This resulted in a classification of 984 wetland polygons and 2,915 non-wetland polygons. In order to achieve near perfect classification accuracy we edited the merged wetland classification through manual photo interpretation of each classified object.

We randomly selected 50% of the classification to use as our validation dataset. From the remaining classification, we selected 400 potential wetlands to use as a training dataset for our Random Forest model. We selected our training data in three ways; 1.) simple random sampling, 2.) stratified random sampling by polygon size into a large (> 2ha.) and small (< 2ha.) objects, and 3.) purposive sampling. The random sampled dataset contained 100 wetlands and 298 non-wetlands. The size-stratified random sample had 199 small polygons and 199 large polygons, which resulted in a sample of 142 wetlands and 256 non-wetlands. The purposive sampling was derived from manually selecting wetlands through visual assessment of the polygons using 1m aerial imagery. The purposive sampling had 100 wetlands and 300 non-wetlands and was meant to mimic a common practice of selecting training data by hand or in the field.

We trained the Random Forest classifier using each of the three sample training datasets. For each RF model we calculated the Area Under the Curve (AUC) and performed an accuracy assessment comparing the modeled results with the validation dataset. Finally, we applied each of the Random Forest model classifiers to the full “*potential wetland*” dataset resulting in three classifications of wetland and non-wetland objects.

2.5.1 Monte Carlo Random Forest Modeling using time series data

In order to understand how the number of satellite image observations improved classification accuracy of our model we iteratively ran our Random Forest model 200 times increasing the number of observations used in the model. For this modeling approach we used the randomly sampled training dataset. We did this iterative process in three ways. 1.) We added each observation into the Random Forest model starting from the beginning of the time series and adding each image observation in sequential order. 2.) We added observations in a random order, and 3.) We added observations from two wet years, two dry years, and two average years of precipitation. For each year we included three observations that captured surface water area in late spring (April – May), early summer (June – July), and late summer (August - September). We plotted AUC, overall accuracy, errors of omission for the wetland class, and errors of commission for the wetland class for each iteration of the three RF models.

3 Results

Our method using OBIA of sub-pixel surface water estimates identified 3,899 polygons as *potential wetlands*. Visual assessment of the polygons using 1-meter resolution aerial imagery identified many false positives that were spectrally similar to wetland inundation. These objects contained materials that absorb light, such as dark pavement, buildings, dark geologic features, and shadows (**Figure 3**). It also classified objects as *potential wetlands* that contained surface water, but aren't considered wetlands, such as irrigated agricultural fields, canals, sections of streams, and rivers (**Figure 3**). These areas were not masked out using any of our ancillary data products.

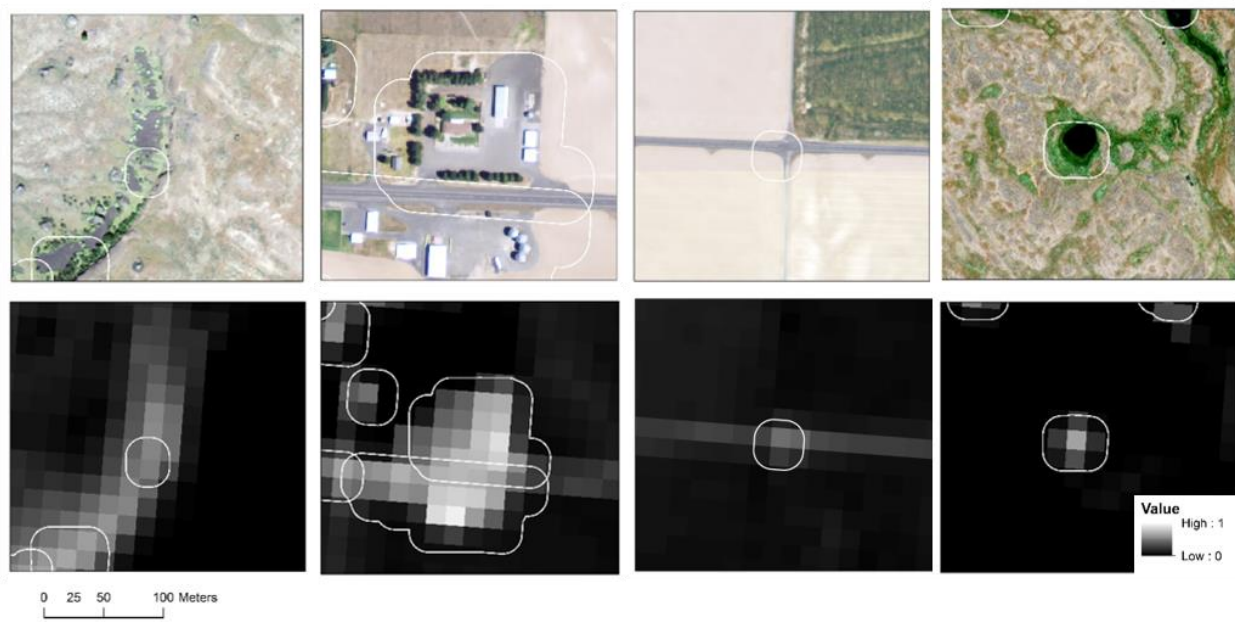


Figure 3. Example of objects classified as *potential wetlands* based on their spectral similarity to inundated wetlands. The top panel shows the segmented feature (white polygons) with an aerial image used as a background to show high detail. The bottom panel is of the same features as detected using the summarized Landsat spring imagery from the 1990s. The potential wetlands represent many false positives that were mapped based on their spectral similarity to water; dark rocks, residential buildings, and an intersection of a road. All of these objects were mapped as potential wetlands, but only the object on the far right represents a true wetland.

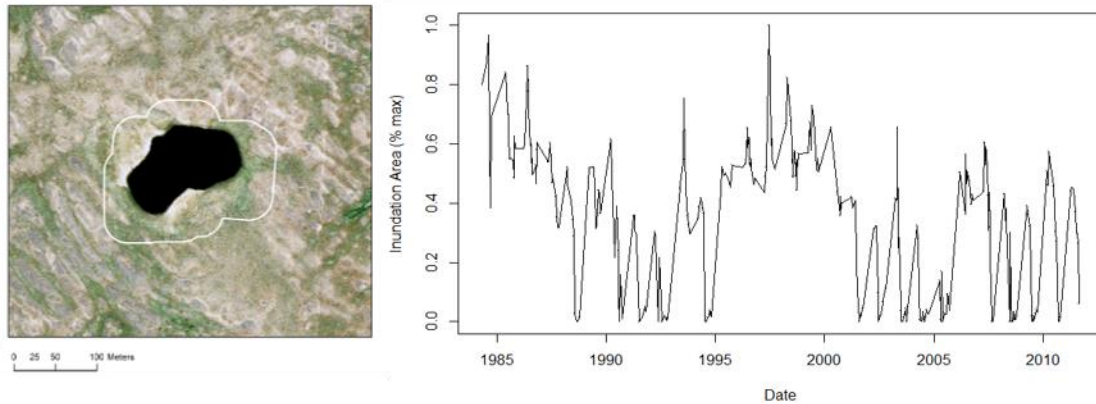


Figure 4. Example of one hydrograph derived from OBIA and spectral mixture analysis showing both seasonal and long-term changes in inundation area.

For wetlands, the changes in surface water area calculated through spectral mixture analysis represented seasonal and long-term changes in surface water inundation (**Figure 4**). Note, that during wetter periods (e.g. 1996 – 2000) this wetland does not dry out, whereas seasonal drying is common at other times. Spectrally similar *potential wetland* objects did not have a similar seasonal or long-term temporal pattern (**Figure 5**).

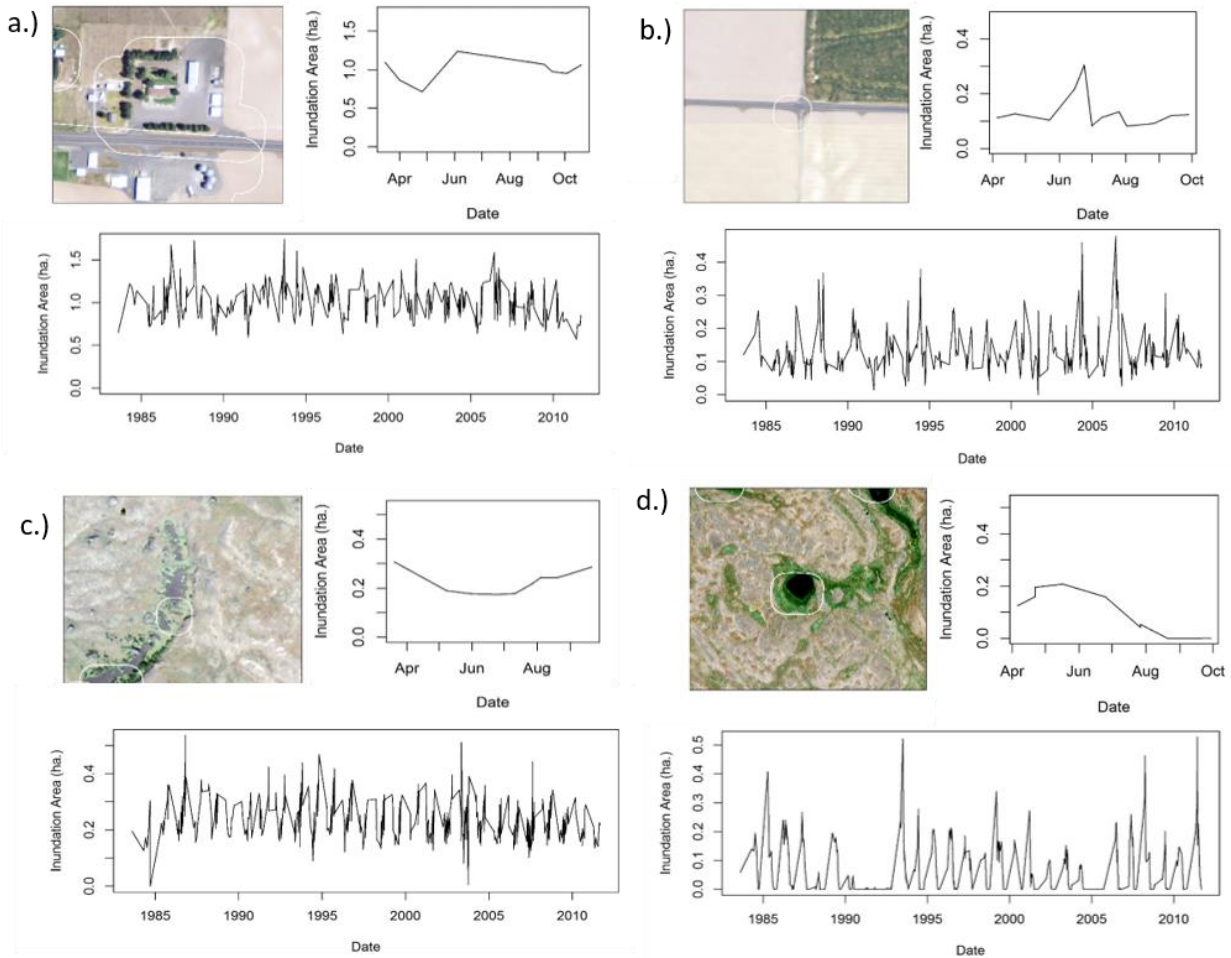


Figure 5. Seasonal and long-term temporal patterns derived from the times series of Landsat imagery for four objects initially classified as *potential wetlands*; residential building (a), dark pavement (b), dark geologic features (c), small wetland (d).

3.1. Question 1 - what is the best sampling design for collecting training data to be used in Random Forest classification of wetland objects

The sampling design for selecting training data for our Random Forest model did not have a statistically impact on overall accuracy of our modeled classification. There was no statistical difference in AUC between the random sample (95% CI: 0.945-0.966) or the random sample stratified by size (95% CI: 0.937-0.961), while the AUC for the purposive sampling was slightly lower (95% CI: 0.9202-0.945) (**Figure 6**).

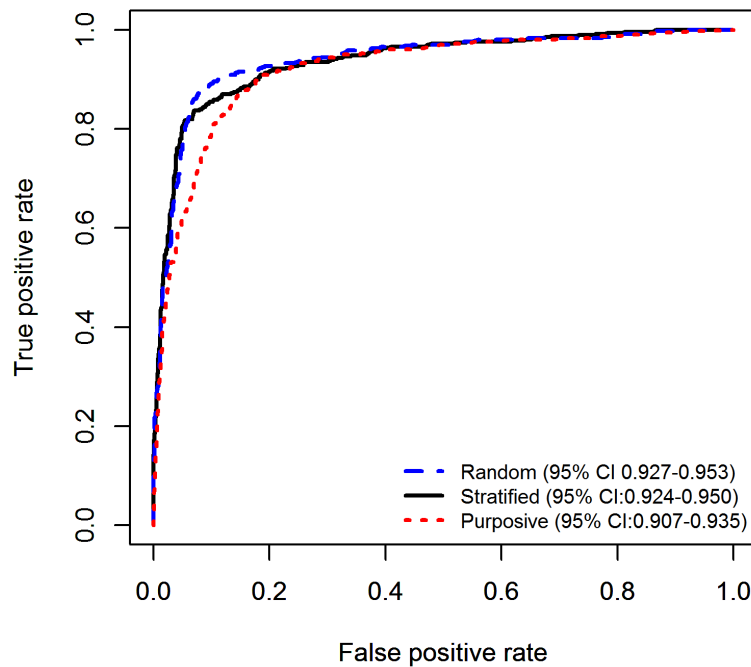


Figure 6. The receiver operating characteristic (ROC) for the three sampling methods, random, stratified, and purposive.

The overall classification accuracy was 91.52%, 92.1%, and 86.0% for the random sample, stratified sample, and purposive, respectively. The errors of omission and commission for the wetland class were similar for the random sample (23.7%, 12.2%) and the stratified sample (15.0%, 15.6%). For the purposive sample classification the wetland classification errors of omission for were 44.7% and errors of commission were 18.2%. Purposive sampling was biased towards larger, undisturbed wetlands, which are easier to identify through photo interpretation. Therefore, the results from the purposive sampling method were biased towards these kinds of wetlands and failed to identify smaller more ephemeral disturbed wetlands. The random sampling and stratified random sampling method produced similar results, although the stratified random sampling method did a better job at mapping larger wetlands.

Table 2: Accuracy assessment for wetland classification using random sampling

Reference Data				
Classification Data	Wetland	Non-wetland	Total	User's Accuracy
Wetland	413	76	489	84.46%
Non-wetland	89	1368	1457	93.89%
Total	502	1444		
Producer's Accuracy	82.27%	94.74%		
Overall Accuracy	91.52%			

Table 3: Accuracy assessment for wetland classification using stratified sampling by size (< 2ha. >2ha.)

Reference Data				
Classification Data	Wetland	Non-wetland	Total	User's Accuracy
Wetland	434	68	520	83.46%
Non-wetland	86	1358	1426	95.23%
Total	502	1444		
Producer's Accuracy	86.45%	94.04%		
Overall Accuracy	92.09 %			

Table 4: Accuracy assessment for wetland classification using purposive sampling.

Reference Data				
Classification Data	Wetland	Non-wetland	Total	User's Accuracy
Wetland	282	52	334	84.43%
Non-wetland	220	1392	1612	86.35%
Total	502	1444		
Producer's Accuracy	56.18%	96.40%		
Overall Accuracy	86.02%			

Visually, the mapped results did not vary substantially between the three sampling techniques. The output classification using the random sample, captured the variability of wetland types across Douglas County (**Figure 7.**), but did miss some large wetlands. The stratified sample

missed fewer large wetlands, and the purposive sample classified large wetlands, but missed many of the smaller more disturbed wetlands that are hard to identify through manual photo interpretation.

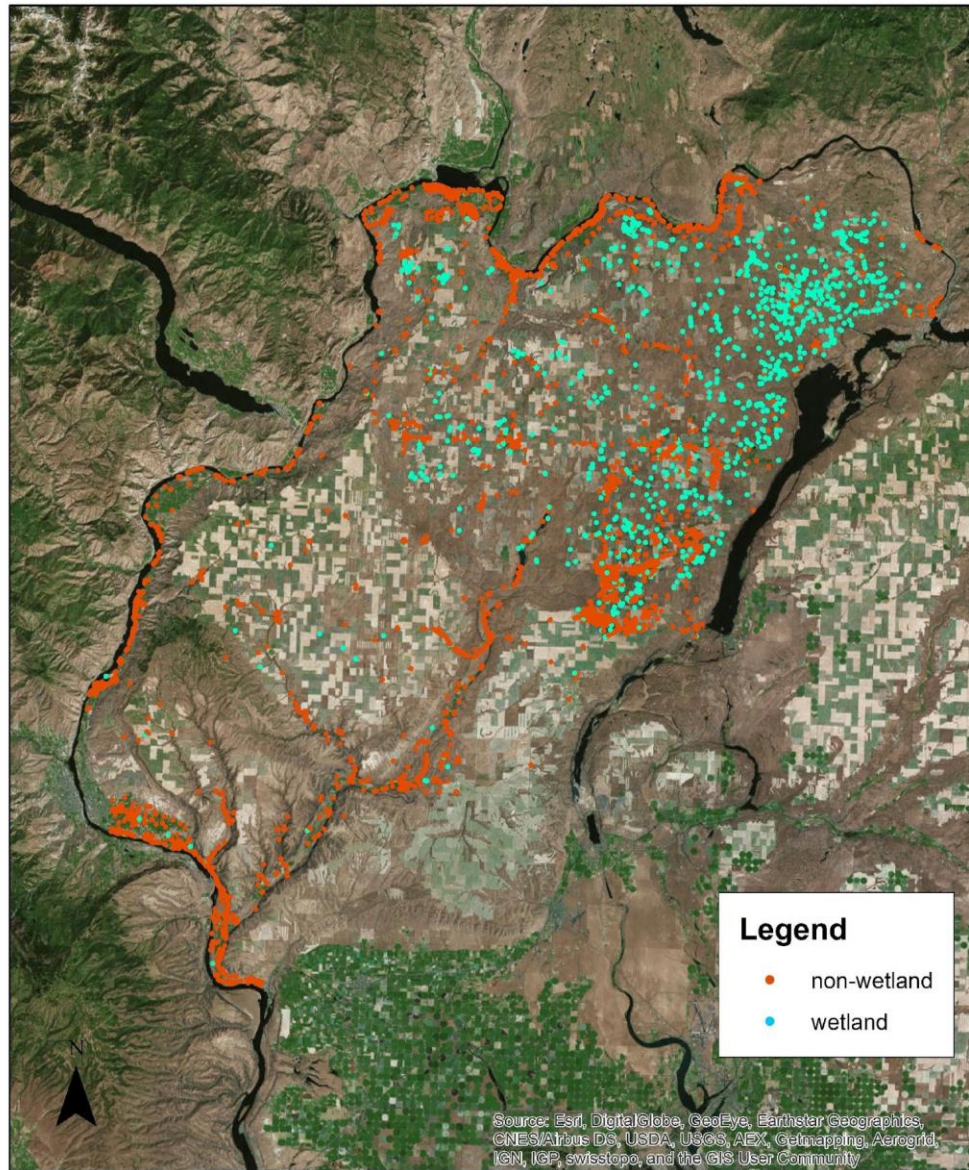


Figure 7. Final classification of wetland and non-wetland based on Random Forest output.

3.2 Question 2 - how does temporal richness (number of satellite observations) impact classification accuracy?

The AUC, overall accuracy, error of omission for wetlands, and error of commission for

wetlands improved when the number of image observations used as predictor variables into the Random Forest model were increased. Increasing the sample size of the training dataset for the RF model did not greatly improve classification accuracy beyond a certain number of image observations. This point of “leveling off” differed depending on how the images were added into the model, sequentially, randomly, or using expert knowledge (**Figure 8**). For randomly selected observations, there was little improvement in skill past 25 observations included, and there was essentially no improvement from either random or sequential methods past about 65 observations included in the training data set. Expert selection methods were not clearly better than random selection in improving skill.

It took approximately 65 image observations to reach this leveling off point if images were added sequentially, it took roughly approximately 40 image observations if images were added randomly. Images added through expert knowledge came close to reaching overall accuracy achieved through a longer time series reaching an overall accuracy of 87.98% although overall accuracy of 87.92% was reached after only 8 image observations were added. Note, however, that a random sample achieved essentially the same level of performance as the expert knowledge approach when about 10 image observations were used as the training data set. Similar relationships were found between number of image observations used and errors of omission and commission (**Figure 9**).

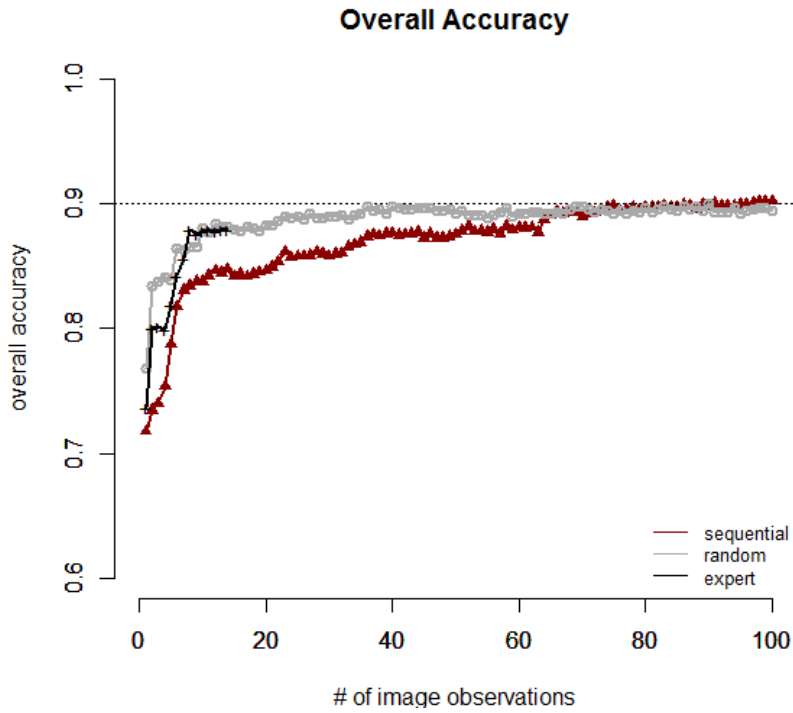


Figure 8. Overall accuracy for wetland and non-wetland classification based on Random Forest models trained on varying numbers of image observations.

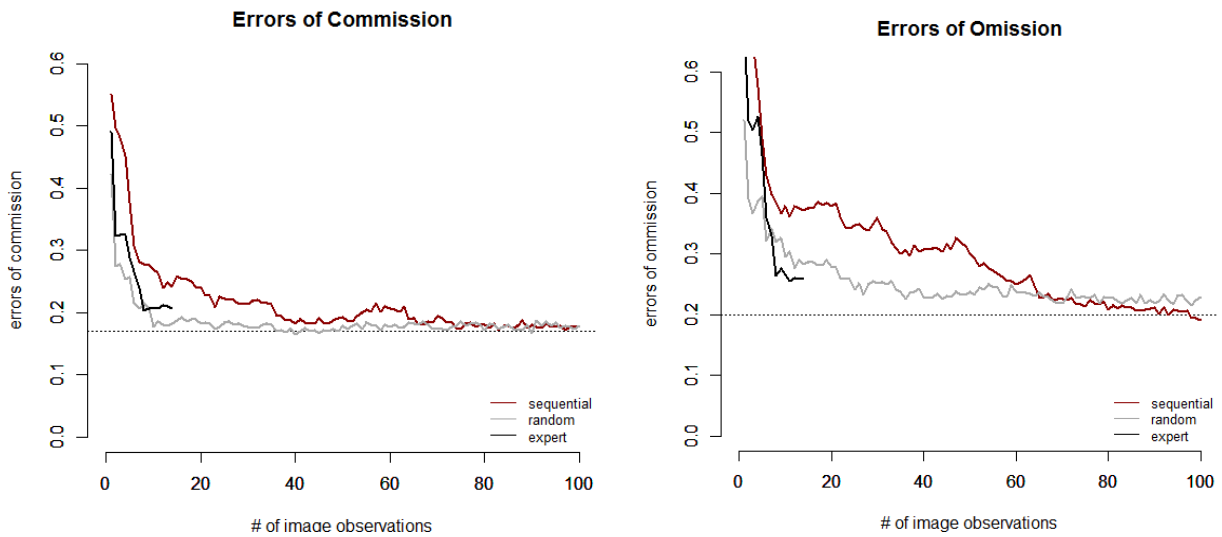


Figure 9. Errors of commission (left) and omission (right) for wetland class based on Random Forest output for each model iteration. We ran the RF model iteratively increasing the number of image observations used by one.

4 Discussion

Our RF model was easy to implement and did not require complicated modeling of the time series patterns themselves. By including the temporal dimension into our OBIA we were able to detect small ephemeral wetlands and remove false positives despite the fact that the Landsat satellite imagery we used had a low spatial resolution. Wetlands composed of only a few Landsat pixels could be detected based on their strong temporal pattern.

Because we were interested in mapping all wetlands, including small, ephemeral wetlands at scales below one or two Landsat pixels, therefore we chose a low threshold (40% surface water cover during the spring) for our initial classification of *potential wetlands*. Because of our low threshold we also mapped a relatively large number of false positives. These objects might not have been mapped if we had used a higher threshold value. Future work to optimize this threshold might be productive in reducing the number of false positives selected at the outset, with resultant improvements in computational efficiency in carrying out subsequent steps.

Our comparison of the three sampling methods (random, stratified, purposive) used to select training data for our RF model did not produce large differences in overall classification accuracy or AUC. However, differences in wetland classification errors of omission were much larger between sampling methods (random 23.7%, stratified 15.0%, purposive 44.7%). This may be due to the fact that wetlands only represented 33.7% of the total potential wetland objects. While the randomly selected training data had a high overall accuracy it did have noticeable errors of omission, particularly a few large more permanently flooded wetlands were mapped as non-wetlands. These kinds of errors may be driven by the indiscriminate selection associated with random sampling. Because small wetlands are more numerous in our study area there was a greater likelihood of randomly selecting small wetlands than larger wetlands. Therefore, the RF model trained on a random sample may have not captured the full variability of larger wetlands causing them to be omitted from the classification. While stratifying the sample by large and small wetlands did not affect overall accuracy it did correct some of these effects and correctly mapped more of these large wetlands. The RF model based on a random sample had the most balanced wetland classification error of omission and error of commission. A stratified sample would be a better choice if it would be worse to omit a large wetland than a small wetland from classification. Another way to remedy this issue would be to run two Random Forest models on

small and larger wetlands separately. Increasing the overall sample size may also reduce the importance of this effect.

In many cases it is hard to get reliable wetland data for training and validation of OBIA classifications. Our purposive sampling strategy represents a common practice among analysts where budget and time constraints may not allow for the collection of new randomly sampled training data. Often existing wetland datasets are biased towards larger more intact wetlands that are easier to identify in aerial imagery or on the ground. While the results from our purposive sampling did create biased results with relatively high errors of omission, it had a high overall accuracy. While purposive data can and should be corrected and updated to reduce this bias, it may be an acceptable practice if constraints exist to limit collection of new field data, as long as the training bias is understood.

Our results demonstrate that the entire time series of Landsat satellite imagery is not required to identify wetlands from spectrally similar landscape features. However, temporal richness can improve accuracy of a classification up until a point where accuracy improvement levels off. The biggest driver of this change was in decreasing errors of omission. A random selection of image observations spanning the entire time series is the best way to capture temporal variability of wetland objects. Therefore, this approach should apply to areas with sparse data or frequent cloud cover as long as data is rich enough to capture the temporal variability of the objects of interest. A random selection of image observations is a straightforward way to characterize wetlands and had higher overall accuracy and lower errors of omission and commission than when observations are selected through expert knowledge (as is common practice). Our analysis also confirms, however, that the practice of selecting image observations from a wet, dry, and average year precipitation can capture most of the variability unique to wetlands.

We were interested in mapping all wetlands, including small, ephemeral wetlands at scales below one or two Landsat pixels, therefore we chose a low threshold (40% surface water cover during the spring) for our initial classification of *potential wetlands*. Because of our low threshold we also mapped a relatively large number of false positives. These objects might not have been mapped if we had used a higher threshold value. Future work to optimize this

threshold might be productive in reducing the number of false positives selected at the outset, with resultant improvements in computational efficiency in carrying out subsequent steps.

We created a simple classification of wetlands and non-wetlands. A further step would be to characterize each wetland by its hydrologic regime. This can also be derived from the time series of inundated area either through use of the entire time series (Halabisky et al 2016) or alternatively by analyzing sets of image observations (Gabrielsen et al 2016).

A key strength to OBIA methods compared to pixel-based approaches is the ease in which data of varying resolutions can be combined so that the object can be characterized by the spatial, spectral, and temporal patterns associated with that object. Once an object is delineated the data can be summarized at the object level, despite the varying differences in resolution. In this study we did not combine datasets together, focusing solely on the temporal resolution of wetland objects. Additional data optimized for other resolution domains could further characterize landscape features. For example, in order to get more precise wetland delineations higher spatial resolution could be included, hyperspectral imagery could be used to characterize wetland by species type, and lidar or radar could be added to characterize a wetland by additional hydrologic processes.

6 Conclusion

This research demonstrates that objects, even small ones consisting of a few pixels, can be classified using the temporal domain. Our method using time series observations as input variables into a Random Forest model was an easy way to classify objects by exploiting their temporal pattern. After more than 40 years of observing the earth from remote sensing platforms we now have a sizeable archive of temporal data cataloging ecosystem change ranging from decadal to daily time steps (Wulder et al 2014). In the last decade, this archive has become increasingly accessible (Turner 2013). Most notably the entire Landsat satellite archive is now freely available. Tools such as Google Earth Engine and the USGS batch download tool provide easy access to time series archives (Pekel et al 2016). Parallel processing and cloud computing allows for rapid analysis of time series data. While time series analysis has been part of remote sensing for many decades, with improved computer processing and increased availability of time

series datasets it is now much easier to incorporate temporal characteristics into OBIA. This research demonstrates that objects, even small ones consisting of a few pixels, can be classified using temporal pattern.

7 Acknowledgments

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Chapter 3. Projecting the hydrologic impacts of climate change on wetlands in the Columbia Plateau ecoregion

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Abstract

Depressional wetlands in the Columbia Plateau are valuable habitats because of their ability to maintain surface water into or throughout the dry summers. The source of that moisture, which can be surface runoff from surrounding areas, groundwater in local aquifers, or a combination of both, may determine if these wetlands are seasonal (drying up each year), permanent (maintaining surface water from year to year), or semi-permanent (drying up some years but not others). To manage and restore these wetlands so that they continue to provide habitat and other services requires understanding how these flooding and drying patterns (their hydrologic behavior) have changed in the past, and how projected changes in climate might affect them. The goal of this project was to provide just such understanding, in the form of spatially complete

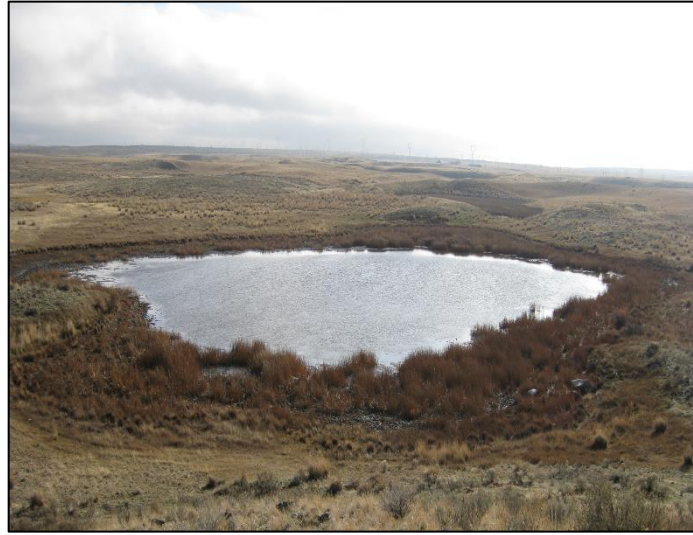
maps of wetlands across the region, coupled with detailed 30-year hydrographs of historical (1984-2014) fluctuations in water extent for each of those wetlands, developed using remote sensing techniques. We combined these observed data with 30-year simulations of historical (1984-2014) and future (2070-2099) conditions using the Variable Infiltration Capacity (VIC) hydrologic model, which calculates soil moisture, evapotranspiration and other water balance variables as a function of climate, land cover, and soils. Using these combined observed and simulated data resources we developed statistical models that captured the relationship between the remotely-sensed surface water extent and the VIC water balance variables for the historical time period. By running VIC using projected future climate, and then applying our statistical models to the resulting water balance simulations, we were able to make projections of expected water extent for the projected end-of-the-century climate. Our findings suggest that wetlands in the Columbia Plateau will respond quite differently depending on the influence of groundwater sources and water storage ability, which varies greatly throughout the region. In general, groundwater driven wetlands, which tend to be more permanently flooded, will increase in water levels & dry less frequently. Surface water driven wetlands, which tend to be more seasonally flooded, will experience decreasing water levels, dry more frequently, & dry earlier in the season, or have little change. We engaged with a range of wetland practitioners throughout the project, worked with them to interpret the results, and to apply an approach to using data such as these to evaluate potential management and restoration actions and their long-term consequences in a changing climate.

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Introduction

Wetlands are valuable ecosystems that benefit society. They allow for gradual recharge of groundwater, control erosion, mitigate water pollution, provide water storage, support food and recreational bases for people, and play an important role in biogeochemical cycles (Bolund and Hunhammar 1999; Zedler and Kercher 2005). Additionally,



wetlands are among the most biodiverse ecosystems in the world, due largely to their dynamic hydrologic response to changes in the environment (Mitsch and Gosselink 2007), such as changes in precipitation, evaporation, groundwater levels, or land use. Because many of these factors are affected by climate, wetlands are considered to be especially sensitive to climate change (Larson 1995; Winter 2000; Johnson and Poiani 2016). A small change in precipitation or evaporation—which is dependent on temperature, among other factors—can alter wetland hydrologic response, which in turn impacts important ecological processes that define ecosystem function of across the landscape (Rover et al 2011; Werner et al 2013; Schook and Cooper 2014; Ray et al 2016).

Despite the importance of wetlands, over 50% of the wetlands within the continental United States have been drained or filled since pre-colonial times (Dahl 1990). While policies have been enacted to slow the loss of wetland habitat, wetlands are often surrounded by highly modified landscapes that impact their condition and function (Pavri and Aber 2004; Zedler and Kercher 2005). Therefore, in order to protect the health and function of wetlands, natural resource managers must control for myriad indirect stressors, such as pollution from agricultural or urban runoff, habitat fragmentation, and invasive species (Zedler and Kercher 2005; Gleason et al 2011; Anteau et al 2016; Calhoun et al 2016). While most managers realize the importance of including climate change impacts in their management of these systems, the data and tools to do this have largely been unavailable to practitioners who manage or restore wetlands.

In arid and semi-arid regions like the Columbia Plateau the hydrology of wetlands is in constant flux as they flood and dry up throughout the year. Wetlands, even in close proximity to each other, can show very different hydrologic behavior depending on the source of their major hydrologic inputs (i.e. precipitation, groundwater, surface water) and other factors that influence the inflow and outflow of water (e.g. basin size, soil types, geology)(Winter 2000; Winkler et al 2010). Generally, depressional wetlands fall along a continuum from those driven mainly by surface water fluxes to those driven mainly by groundwater fluxes (Euliss et al 2004). Each wetland falls at a different point along this continuum due to surface and subsurface flows and deeper groundwater flowpaths that vary over time (Euliss et al 2004; Rains et al 2015). Wetlands driven primarily by surface water inputs tend to have a rapid response to changes in precipitation and evapotranspiration and may fluctuate greatly from season to season (seasonal scale). At the other end of the continuum, wetlands driven primarily by groundwater sources may vary slowly over multiple years (multi-year time scales) due to a higher water storage ability (Winter and Rosenberry 1995; Schook and Cooper 2014).

The dynamic nature of wetlands leads to great variability across locations and through time, within and among wetlands. This variability, combined with a lack of frequent observations taken over long time periods, makes study of these ecosystems particularly challenging. In order to measure wetland hydrodynamics through traditional, field-based procedures requires frequent visits to many sites across a landscape or establishment of expensive field sensors. Physically-based models that are calibrated with field data require an understanding of all the factors that influence wetland hydrology, some of which are difficult to measure (e.g. groundwater inputs). It is also challenging to scale up such models across all wetlands in a large landscape while still preserving the variability inherent to wetlands, as the importance of those factors can vary significantly from wetland to wetland.

Existing remote sensing data and methods can help address this lack of detailed information on wetland hydrologic behavior. After more than 40 years of observing the earth from remote sensing platforms we now have a sizeable archive of data cataloging ecosystem change at decadal, annual, seasonal, and sometimes even daily time steps (Wulder et al 2014). In the last

decade, this archive has become increasingly accessible. Most notably, the entire Landsat satellite archive is now freely available. Landsat images show land surface characteristics for pixels 30 meters on a side, and fly over the same area every 16 days, beginning in 1972 (although imagery greatly improved with deployment of the Landsat Thematic Mapper in 1982). In this project we use the Landsat archive to map wetlands across the Columbia Plateau Ecoregion, and to reconstruct their hydrologic dynamics over a 30-year time period (1984-2011).

Patterns in precipitation and evapotranspiration—which is dependent on temperature, among other factors—are changing across the globe (Arnell et al 2001; Ciais et al 2013; Abatzoglou et al 2014). The resulting dynamics of depressional wetlands are therefore likely to be impacted by such changes in climate. There are a few notable long-term studies of climate change impacts to wetlands; however, those that exist only sample a relatively small number of wetlands (Johnson and Poiani 2016) and then attempt to extrapolate findings to the broader landscape scale. While such studies are useful at understanding general landscape patterns, due to their narrow scope they tend to miss important wetland specific details, such as identifying where a wetland falls on the surface water to groundwater continuum and how climate will influence its unique hydrologic dynamics. Even in areas where we understand how the climate is changing, and have quantified these changes through climate change projections, we cannot necessarily translate this information to assess impacts on specific wetlands because of the necessary data at this finer scale—the scale of each wetland—is unavailable.

This lack of wetland-specific information on climate change impacts is a problem highlighted by land managers across the Columbia Plateau. As a result, although general strategies exist for reducing impacts of climate change on wetlands, on-the-ground efforts are seriously hindered by a lack of the basic information needed to understand where to implement those strategies with some expectation of long-term success. This weakness in our collective ability to understand, manage, and adaptively plan for wetlands threatens to compound the massive losses of wetlands and wetland function that have already occurred (Dahl 1990). By using the reconstructed hydrologic dynamics of wetlands to evaluate and calibrate a climate-hydrologic model of wetland behavior, this project provides insights into wetland-specific and landscape-wide patterns of change in wetland dynamics that can be expected in a changing climate.

Project Objectives

The overall goals of our project were three-fold: First, to provide consistent, spatially complete data on wetland location and historical hydrologic dynamics using remotely sensed data. Second to project climate change impacts on hydrologic dynamics for individual wetlands over the same domain. Third, to work with managers in using these data, so that they could translate existing, general climate change strategies to specific actions that support climate-smart management and conservation of specific wetlands across the Columbia Plateau.

Specific project objectives to achieve these goals were to:

- 1) Map wetlands across the Columbia Plateau using a time series of Landsat satellite imagery.
- 2) Reconstruct surface water hydrographs of each individual wetland over the entire ecoregion from 1984 to 2011, and use the reconstructed hydrographs to classify wetland types.
- 3) Measure historical changes to wetland surface water area from 1984 to 2011.
- 4) Project future changes in the hydrodynamics of wetlands using downscaled climate models for the 2080s.
- 5) Identify hotspots of management concern by mapping regional wetland dynamics across the Columbia Plateau using historical and projected hydrographs.
- 6) Collaborate with land managers to identify climate-smart actions to conserve wetlands in light of expected climate change impacts.

Study Area

We conducted our analyses in the Columbia Plateau Ecoregion, a semi-arid landscape in the northwest of the United States (**Fig. 1**). The Columbia Plateau is a region with strong human influences on wetland hydrology such as land conversion, runoff from irrigated agriculture, ditching and draining, and groundwater withdrawal. Geographically isolated, depressional wetlands are the dominant wetland type. Seasonally, refill of wetlands in this area is typically driven by snowmelt and precipitation occurring in late winter or early spring. As the summer season progresses, temperatures increase and precipitation levels decline. Wetlands begin to dry

out during this time, with many wetlands completely dry by the end of the summer. Short-term rainfall events occur sporadically during the spring and summer months and are usually localized in nature. These events rarely lead to re-wetting of wetlands that have already dried for the season.

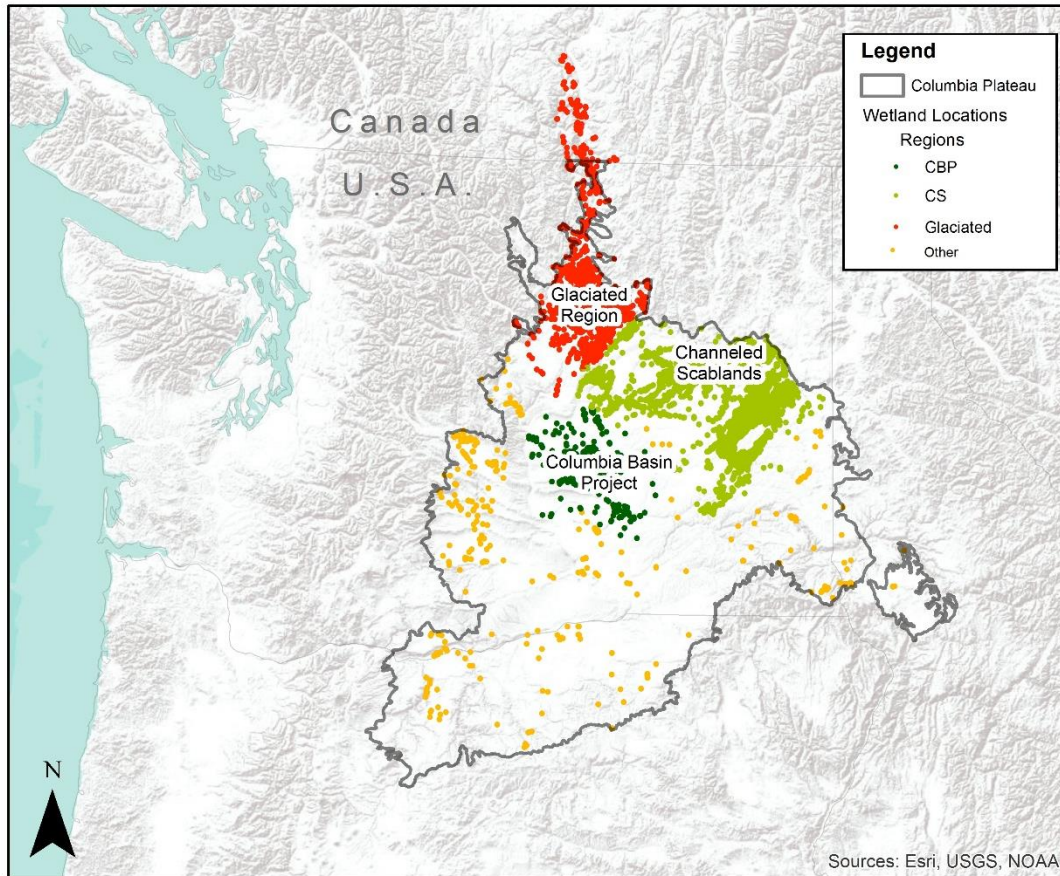


Figure 1. Locations of wetlands by region in the Columbia Plateau ecoregion.

Several geologic and human initiated events have created a diverse landscape, influencing the spatial distribution of wetlands and wetland types across the Columbia Plateau. We refer to these three regions as the Glaciated region, the Channeled Scablands, and the Columbia Basin Project:

- 1) **Glaciated region:** This region of the Columbia Plateau was glaciated during the last ice age approximately 20,000 years ago, which created a topographically complex area with perched aquifers and intricate subsurface flows, and a high density of depressional wetlands. This region includes the area around northern Douglas County, the Colville

Indian Reservation, and continues north into British Columbia, Canada (see red wetland locations in **Fig. 1**).

- 2) **Channeled Scablands:** This region was created by a series of massive floods between 18,000 and 13,000 years ago, which scoured parts of the Columbia Plateau. This area includes the area around Banks Lake, the areas surrounding Swanson Lakes, and the areas near the cities of Spokane and Cheney (see light green wetland locations in **Fig. 1**).
- 3) **The Columbia Basin Project (CBP):** The CBP is an irrigation development project that began bringing water from the Columbia River to agricultural lands in the central region of the Columbia Plateau in the early 1950s. The CBP caused groundwater levels to rise, which in turn supplemented existing wetlands and established new ones. Most of the wetlands in this area are groundwater driven. The Columbia Basin Project intersects with parts of the Channeled Scablands. In these overlapping areas influences from the CBP override the natural conditions. In using the term CBP we only refer to the areas in the CBP that have already been developed through surface water irrigation (see dark green wetland locations in **Fig. 1**).

Methods

We analyzed the flooding and drying patterns of 5,382 wetlands from 1984 to 2011 across the Columbia Plateau Ecoregion. We created this dataset using methods described in detail in Halabisky et al. (2016) and Halabisky et al. (in prep). The basic steps, described in more detail below (**Fig. 2**), are:

- 1) *Reconstruct wetland hydrographs:* We used a time series of Landsat satellite imagery (1984 – 2011) to detect and delineate wetlands and to reconstruct individual wetland hydrographs.
- 2) *Develop wetland-specific regression models:* We then used the reconstructed hydrographs along with the Variable Infiltration Capacity (VIC) hydrologic model to develop wetland-specific regression models for each wetland relating climate variables to changes in wetland inundation.
- 3) *Classify wetlands:* Next, we classified wetlands in two ways: by their hydrologic regime—seasonal, permanent, or semi-permanent wetlands—and by the primary hydrologic input—groundwater or surface water.

- 4) *Hindcast and forecast wetland hydrology:* Finally, we used the wetland-specific regression models to hindcast (modeling back in time, to see how well the model can “predict” the fluctuations that actually happened historically) and forecast (making projections of hydrologic fluctuations into the future, under a changing climate) changes in the hydrodynamics of each wetland.
- 5) *Estimate change in key wetland dynamics metrics:* We examined the changes between hindcast and forecast hydrographs—from historical data based on 1980s climate to future data based on 2080s climate—across the Columbia Plateau.
- 6) *Identify hotspots of management concern:* We mapped regional wetland dynamics across the Columbia Plateau using the historical and projected hydrographs. Patterns of change across the landscape provide guidance on which areas or wetland types are likely most vulnerable to climate change impacts.

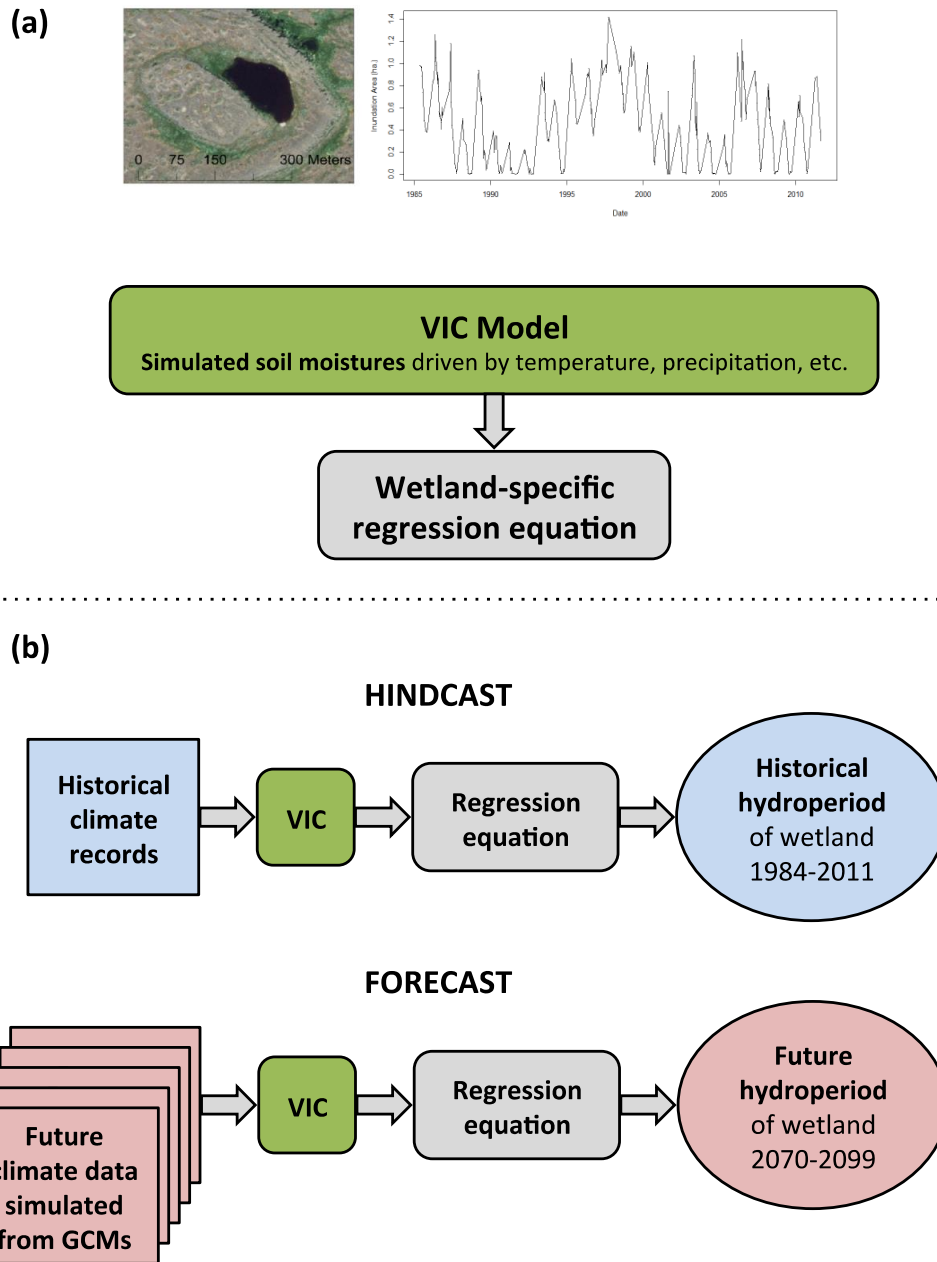


Figure 2. Schematic diagram of the method of projecting and hindcasting wetland hydrology using the VIC hydrologic model, calibrated with the remotely sensed hydrologic data (a) and driven by historical or simulated future climate inputs (b). Figure adapted from Lee et al. (2015).

Our methods generated projections of change in wetland hydrodynamics at two spatial scales: a) for individual wetlands and b) at a landscape scale. This report therefore organizes the results around these two spatial scales.

Reconstructed wetland hydrographs

We delineated wetlands and reconstructed individual wetland hydrographs using a time series of Landsat satellite images spanning 27 years (1984 – 2011). Because many wetlands are small and changes to surface water area occur at scales smaller than the size of a 30-meter Landsat pixel, we used a sub-pixel technique called spectral mixture analysis (SMA)(Adams and Gillespie 2006). SMA estimates the proportion of different surface materials contained within a pixel by comparing the mixed spectral signature of that pixel to a set of “pure” reference spectra.

We identified and delineated wetlands from the Landsat time series of sub-pixel surface water estimates, through a pattern recognition technique called object based image analysis (OBIA). OBIA differs from other pixel-based remote sensing techniques by aggregating pixels with similar characteristics into segments or polygons (Blaschke 2010). We created polygons by selecting and grouping pixels that on average had at least 360 m² of the area (40% of a pixel) measured as surface water, from April 1 to June 1, which we considered to be potential wetland objects. We identified 51,940 potential wetland objects. These were considered “potential” wetlands because an object may be falsely identified as a wetland when its spectral signature is similar to that of water. Features such as shadows and dark rocks are examples of objects that have spectral signatures similar to water’s. Additionally, open water wetlands may be spectrally identical to other water features such as canals.

In order to remove these “false positives”, we further characterized wetlands by their pattern of flooding and drying over time. Dark rocks, for example, will not vary from image to image in the way that surface water area grows and decreases through each season. Distinguishing wetlands based on their temporal pattern allowed us to map wetlands without the necessity of running computationally-intensive methods using high resolution aerial imagery (which is also possible, see Halabisky et al. 2011). Based on these temporal patterns, each wetland was given a probability score, from 0-1, which is an estimate of its likelihood of actually being a wetland. We

selected wetlands that had more than a 0.5 probability of being a wetland, which reduced our dataset from 51,940 to 5,382 wetlands.

Once each wetland was identified and mapped, the corresponding sub-pixel surface water estimates derived from the Landsat time series was used to reconstruct a surface water hydrograph spanning from 1984 to 2011. Our previous research had demonstrated that this method provides highly accurate surface water estimates for each wetland in a Landsat image scene ($r^2 = 0.98$), which can then be used to create long-term surface water hydrographs for individual wetlands (Halabisky et al 2016).

Wetland-specific regression models

We developed wetland-specific regression models that relate the remotely-sensed surface water area of a wetland to water balance variables derived from the VIC hydrologic model (see details in *Box 1 – The Variable Infiltration Capacity Model – Inputs and outputs*), obtained when the VIC was run using precipitation and temperature for the same time period for which we had remotely sensed surface water area estimates. We used step-wise regression to select the two best predictors for each wetland. Possible predictor variables were those obtained from the VIC output. The surface water observations derived from the Landsat time series (1984 – 2011) were used as the response variables. Predictor variables and the resulting regression models were developed independently for each wetland.

Box 1 – The Variable Infiltration Capacity Model – Inputs and outputs

The VIC model is a physically based hydrologic model that, when given information of precipitation, temperature, and other climatic variables, calculates different water balance variables that affect wetland hydrology, for each location across the landscape. Input variables therefore include daily meteorological data—precipitation, maximum and minimum daily surface air temperature, and wind speed for each grid cell the model is run on—in addition to soil and vegetation data. Output variables include runoff, baseflow, evapotranspiration, soil moisture at three different soil depths, as well as the snow water equivalent above the surface (**Fig. 3**). The VIC model has been widely used to assess the hydrologic impact of climate change on a number of watersheds in the Pacific Northwest and across the western U.S. (e.g., Hamlet et al., 2013; Salathé EP, Littell J, Mauger GS, Lee SY, 2013; Tohver et al., 2014). Recently, the VIC model was used to assess the impacts of climate change on montane wetlands by relating soil moisture in the bottom (deepest) soil layer, which is one of outputs from the VIC model, to observed wetland water levels collected in the field (Lee et al 2015).

For our analysis, we modified the algorithm used to characterize the relationship between wetland water level and deep soil moisture estimates, developed by Lee et al. (2015). In addition to using three VIC output variables—soil moisture at three different soil depths—we also calculated two additional variables, derived from the VIC precipitation and evapotranspiration variables: cumulative deviation from mean precipitation (CDFM) and cumulative deviation from mean precipitation minus evapotranspiration (CDFMP-ET), which can be used as surrogates for modeled groundwater response (Ferdowsian and McCarron) (Ferdowsian and McCarron, 2001; Yesertener, 2007). CDFM assumes that the cumulative departure from mean precipitation explains changes in groundwater levels of an unconfined aquifer. CDFM has been used to project future groundwater levels in various regions (Ali et al 2010). To calculate CDFM, the precipitation for a defined period (daily for this analysis) is subtracted from the long-term mean precipitation of the same period. These differences are then accumulated through time using the same defined time period. For some groundwater driven wetlands where water is stored above ground and the wetland has large areas of open water, evaporation rate plays an important role. Therefore, in addition to the CDFM we calculated the cumulative deviation from the mean using the net water flux (i.e. precipitation minus evaporation, or P-ET). One way to visualize how CDFM works is by imagining a leaky bucket halfway filled up. When precipitation (or P-ET for CDFM P-ET) levels are higher than average the bucket fills up, when precipitation levels are lower than average the water levels decrease.

We calculated Nash Sutcliffe Efficiency (NSE) as well as the Pearson's R value as measures of goodness of fit between observed wetland water level from Landsat images and simulated wetland water levels based on VIC output variables.

Wetland classifications

In order to understand projected climate change impacts for different wetland types, we classified wetlands in two ways. First, we classified the hydrologic regime for each wetland based on the Cowardin classification (Cowardin and U.S. Fish and Wildlife Service, Office of Biological Services, 1987) into three categories: seasonal, semi-permanent, and permanent. A seasonal wetland dries up most years (>75% years), a semi-permanent wetland dries up in some years (< 75%), and a permanently flooded wetland never dries up. We assumed a wetland was dry when it had less than 5% surface water area. We used this threshold because for some wetlands it is difficult to model when a wetland has completely dried out. We calculated the number of years each wetland dried, using these thresholds, based on the hindcast and forecast hydrographs for the time period.

Secondly, we classified wetlands by their primary hydrologic input: surface water or groundwater. This classification was made based on which VIC variable had the strongest correlation to changes in wetland surface water area. We classified wetlands as being surface water driven wetlands

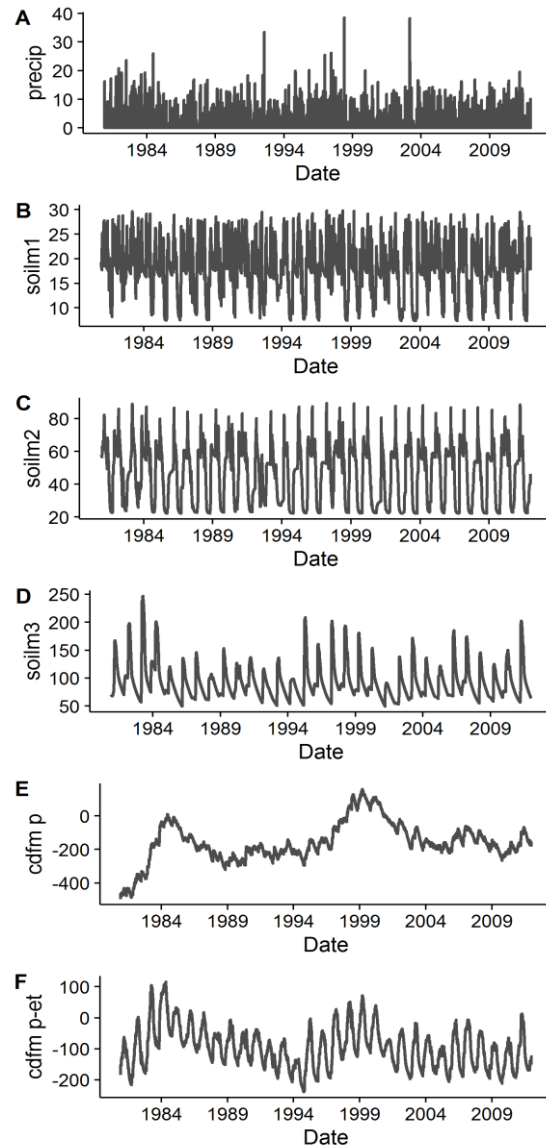


Figure 3. Example of the output variables derived from the VIC hydrologic model from 1984 – 2011. These variables were used as predictors in the wetland-specific regression models. From top to bottom: precipitation, soil moisture in top (soilm1), middle (soilm2), bottom layer (soilm3), CDFMP, and CDFM P-ET. These variables reflect VIC output at one wetland location.

if they correlated best with the VIC output variables associated with seasonal climate variability: soil moisture variables, precipitation) (**Fig. 3**). We classified wetlands as groundwater driven if they correlated best with the variables derived from the VIC output that better reflect multi-year climate variability: CDFM or CDFM P-ET (**Fig. 3**). We mapped the distribution of these two classification schemes across the Columbia Plateau.

Hindcasting and forecasting

For wetlands with good wetland-specific model fit ($r^2 > 0.5$) we used the wetland-specific regression model to hindcast and forecast wetland water dynamics day by day for 30-year historical and future time periods. We hindcasted to fill in missing data (note that Landsat-derived estimates of surface water area provided data points at best every 16 days), extend the time series beyond the years Landsat is available to a longer time period (from 1984 – 2011 to 1915-2012), allowing direct comparison to our projected hydrographs.

Box 2 – Climate change projections used to forecast wetland change by the 2080s

To forecast wetland water dynamics across the CP, we used the ECHAM5 which is a general circulation model (GCM) completed as part of phase 3 of the Coupled Model Inter-comparison Project (CMIP3) (Covey et al., 2003). We chose ECHAM5 as it was the highest-ranked GCM in reproducing the observed Pacific Northwest climate (Mote and Salathe Jr 2010) and it approximates the average precipitation and temperature changes for twenty different GCMs. ECHAM5 A1B scenario uses the Hybrid Delta (HD) method to downscale data to a higher resolution, which enable us to directly compare to the historical record on an event basis from same daily variability.

Appendix A. of Tohver *et al.* 2014 provides the detail of HD method. Briefly, the HD method uses quantile mapping techniques to produce the transformed monthly observed climate data (years 1915-2006) based on a 30-year future time period (i.e. the 2080s or 2070-2099) and then the future monthly values are used to produce a rescaled future daily time series ("1916-2006") for the 2080s needed to drive the hydrologic model. Note, that historical runs were extended from 1915-2006 to 1915–2012 in order to make use of Landsat satellite images (1984-2011). However, for climate change scenarios we used existing data developed by Hamlet *et al.* (2013) that have 92 years of observed variability (1915-2006), projected for future time periods.

We developed the future hydrographs for the period 2070-2099 using climate predicted for the 2080s by projecting surface water area using the wetland-specific regression models, with the water balance variables obtained by running VIC using projected future precipitation and

temperature (see *Box 2 – Climate change projections used to forecast wetland change by the 2080s*). When making future projections we assumed that the fitted regression relationships between wetland response and the selected water balance variables will not change with time. This assumption allows us to use the wetland-specific regression model developed based on the historical relationship between surface water area and VIC outputs, and apply them to estimate surface water area given VIC outputs under future climate projections.

Estimating change in wetland dynamics

In order to examine the patterns of change already observed in the wetlands' historical hydrographs we calculated a trend line for each wetland, based on the remotely sensed observations from 1984 – 2011. We used the slope of this trend line to map the magnitude of wetland change across the Columbia Plateau. Wetlands that had a trend line with a negative slope have been drying over this timeframe, while wetlands that had a trend line with a positive slope have been getting wetter.

In addition, once we had hindcast and forecast hydrographs for each wetland, we also estimated relative changes in key metrics that can be derived from these hydrographs, and were of interest to wetland managers and practitioners in the Columbia Plateau. We calculated the change between historical (1980s) and future (2080s) values for the following metrics:

- **Maximum annual surface water area.** Calculated using the annual maximum extent of inundation for each wetland averaged for all years.
- **Drying frequency.** Calculated based on the number of years out of 100 a wetland has dried (< 5% extent), expressed as a proportion.
- **Seasonal drying date.** Calculated as the first day a wetland dries in a season, and averaged over all years that a wetland dried (<5% extent) during the dry season (March – October).
- **Distribution of wetland types (i.e. seasonal, semi-permanent, permanent).** Calculated based on the change in frequency of each wetland type within each region.

By mapping the relative change in each wetland, we explored patterns of change in wetland dynamics across the Columbia Plateau, identifying areas or wetland types that were expected to change most drastically by the end of the 21st century.

Results and Discussion

Reconstructed wetland hydrographs

Our method using a time series of Landsat satellite imagery to map and reconstruct wetland hydrographs identified 51,940 potential wetlands. The individual hydrographs capture both long-term and seasonal inundation (**Fig. 4**). Different wetlands showed high variability in wetland flooding and drying patterns, with many exhibiting a major human influence (**Fig. 5**).

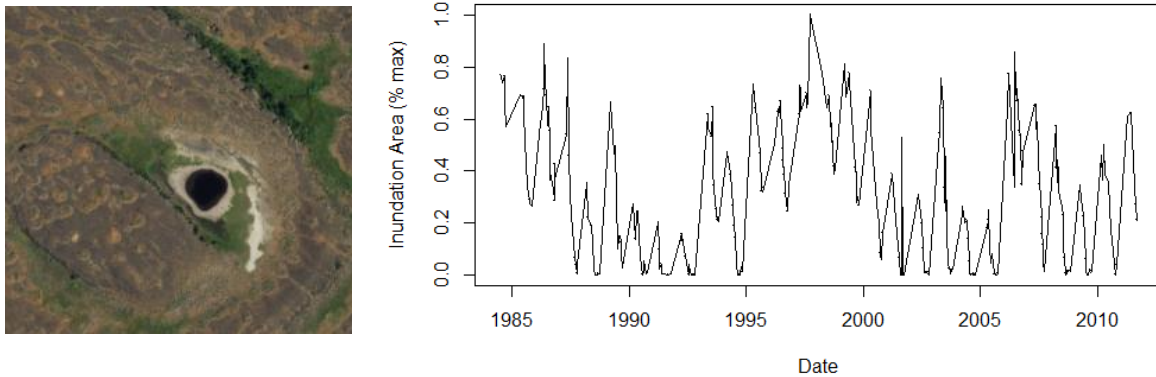


Figure 4: Example of a hydrograph for one wetland created using a time series of Landsat satellite imagery. The hydrograph follows regional climate patterns, increasing in wet periods (~1984, ~1995 – 1997, 2006 – 2009).

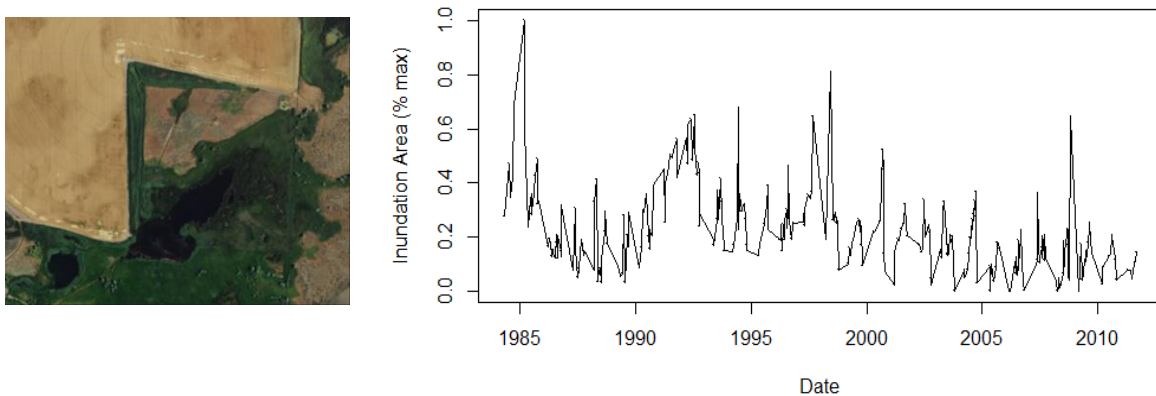


Figure 5: Example of an abnormal hydrograph impacted by irrigated agriculture. The hydrograph does not follow regional climate patterns as the wetland above.

Our process of removing “false positives” through temporal characterization reduced the dataset from 51,904 to 5,382. These 5,382 wetlands have a reasonable likelihood of being “true” wetlands. However, this process also removed wetlands with abnormal hydrologic patterns or ones that were difficult to map. These may include:

- Long, linear wetlands that are hard to delineate using 30 meter pixels. These wetlands sometimes get delineated as multiple polygons, or incorrectly delineated.
- Wetlands with significant shadows from adjacent trees or steep topography that influence the spectral signature’s pattern through time. Shadows absorb light in a similar way to water, and therefore are hard to distinguish from water.
- Wetlands with a strong human influence or significant disturbance.

Wetland-specific regression models

The VIC model was able to reasonably reproduce ($r^2 \geq 0.5$) historical patterns of wetland dynamics for ~30% (1,735) of the total number of wetlands in our wetland dataset (**Fig. 6**). For wetlands with an r^2 value greater or equal to 0.5, we were therefore able to: 1) further assess historical hydrologic patterns, extending the dataset developed through remote sensing (1984-2011) to a longer historical time series (1950-2013), and 2) to assess the climate impacts on wetland hydrodynamics (**Fig.7**).

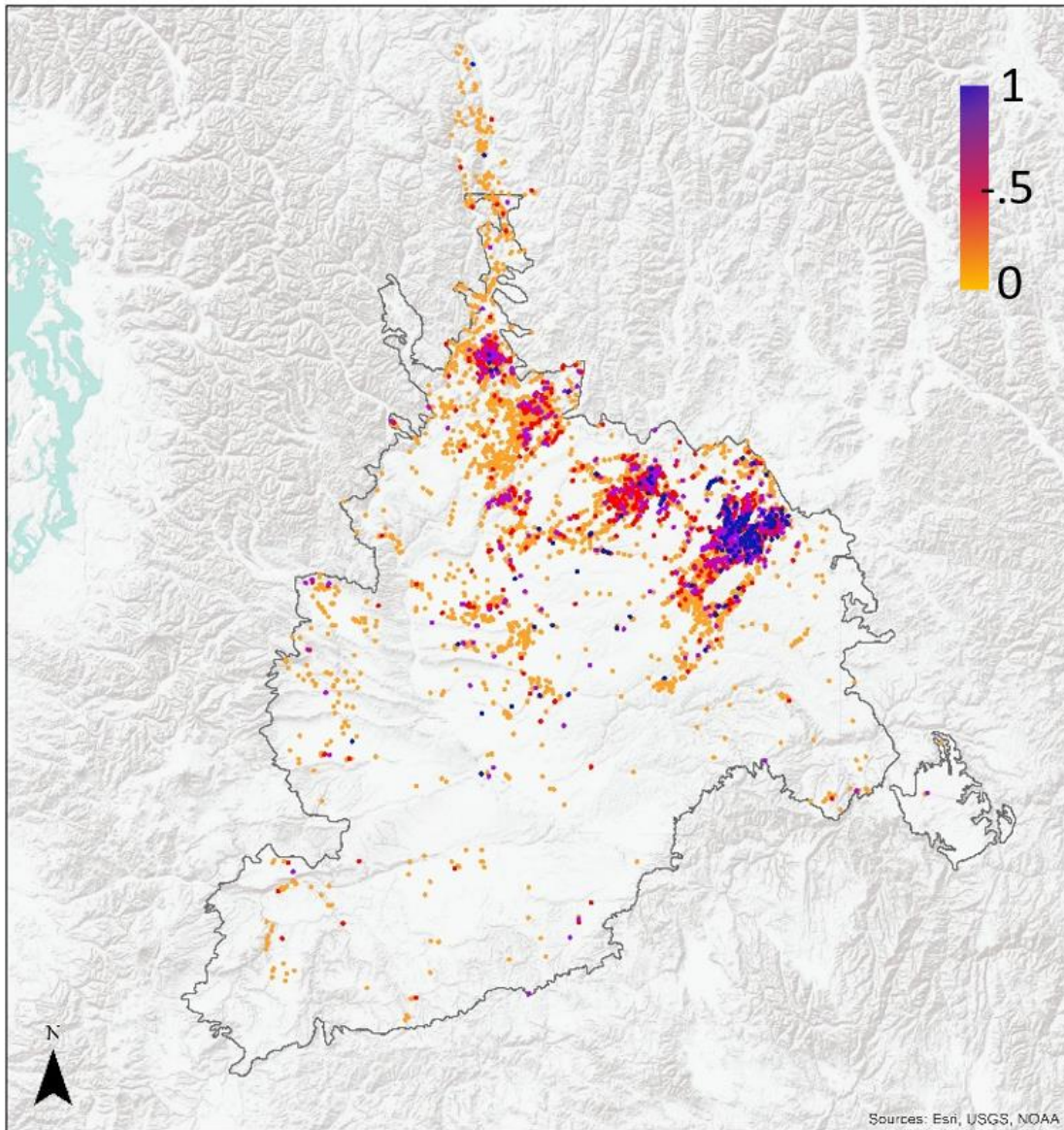


Figure 6. Wetland locations and the r^2 values (0-1) reflecting the goodness of fit of wetland-specific regression models. Potential wetland objects with a probability of being a wetland lower than 0.5 are not shown in this map. Of the wetlands shown, those with wetland-specific models with an r^2 of less than 0.5 were not included in the final analysis of climate change impacts.

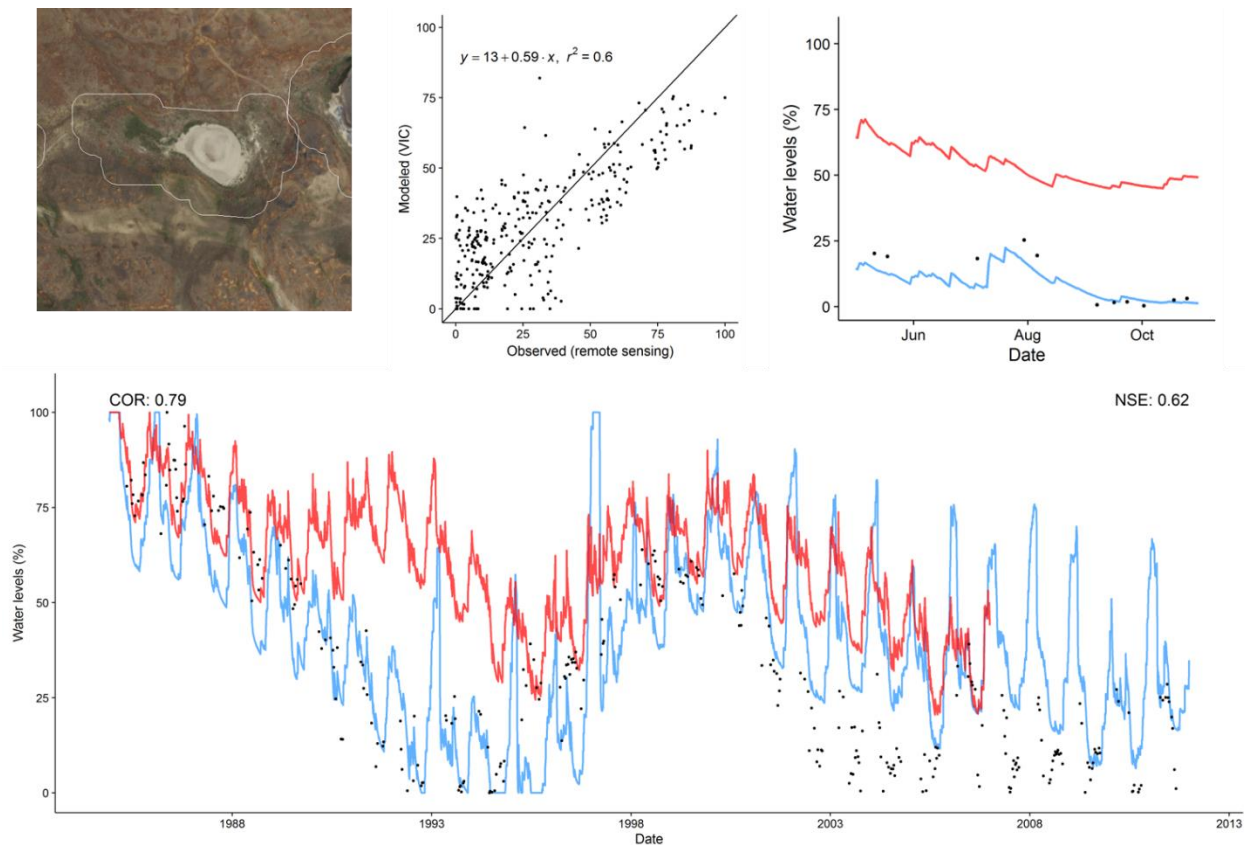


Figure 7. Example of results for one groundwater driven wetland in the Glaciated Region. The upper left panel shows an aerial photo of the wetland. Blue lines represent the modeled hydrograph based on the wetland-specific regression model (hindcasting). Red lines represent the projected hydrograph for the 2080s (forecasting). The upper center panel shows the fit of this wetland’s regression model. In the lower graph, black dots represent surface water area as estimated using remote sensing methods. The upper right panel shows average seasonal drawdown for the 1980s (blue) and 2080s (red). The lower panel shows the observed data, modeled hydrograph, and the projected hydrograph for the 2080s.

We were successfully able to capture the hydrologic behavior of about one third of the wetlands in the Columbia Basin Project region with these methods, however, the remainder of the wetland sites were not suited to this approach as they are driven by deeper groundwater sources and/or artificially influenced by irrigation, both of which the VIC model does not capture.

Low correlation between our predictor variables derived from the VIC model and the remotely sensed response variable (surface water extent) could be due to one or more of the following reasons:

- 1) The predictor variables (e.g. VIC soil moisture in different layers, groundwater surrogates) could not capture the appropriate timing of the inflow and outflow of surface water and groundwater inputs. For example, in many wetlands in the Glaciated Region the groundwater flows are complex and may occur at longer time scales (years or decades) than the variables we used to model groundwater flows, CDFM and CDFM P-ET.
- 2) Wetlands connected to deep sources of groundwater may have a very slow response to climate change. These wetlands tend to be larger in size and to be permanently flooded.
- 3) Other human driven influences, such as groundwater withdrawal and human alterations to the surrounding landscape that may affect surface flows, are not accounted for in our wetland-specific regression models.
- 4) The wetland hydrograph derived from remotely sensed data may contain error from incorrectly delineated wetlands, unmasked clouds, and interference from shadows.
- 5) The remotely sensed methods we used measure changes in surface area, not depth or volume. This could be problematic for deep bowl-shaped wetlands that do not have large changes in surface area.

Wetlands that did not correlate well with our VIC model may still provide useful information on the main hydrologic driver (i.e. groundwater v. surface water), the direction of projected hydrologic change, and the hydrologic regime. Combining these results with local knowledge of the wetland and the surrounding landscape, and examining the dynamics and projections of nearby wetlands with higher model correlation can help managers understand the likely future of the wetland, even if this dataset does not provide explicit estimates of changes due to climate change.

Wetland classifications

Wetlands in the Columbia Plateau fall along a continuum from seasonal to permanently flooded, with no clear breaks between wetland categories. The hydrographs for each wetland varied

substantially (**Fig. 8**), with some wetlands having a rapid response to changes in climate, while others having a lagged response to climatic changes. The lag response to climate is likely due to the time varying hydrologic inputs (i.e. groundwater, surface water) and the factors that affect the rate of inflow and outflow of water in a wetland. Our Cowardin classification resulted in 498 seasonal wetlands, 4,198 semi-permanent wetlands, and 686 permanently flooded wetlands. Semi-permanently flooded wetlands are the most common wetland type in the Columbia Plateau, with enormous variation in the drying frequency within this category. Our secondary classification—based on the dominant hydrologic input—resulted in 1,684 groundwater-driven wetlands and 3,696 surface water-driven wetlands. While this primary input was used to classify the wetlands, it is important to re-emphasize that most wetlands have some combination of both groundwater and surface water inputs (**Fig. 8**). Our two classification systems are strongly related each other. Groundwater driven wetlands tended to be more permanently flooded, while surface water driven wetlands tended to be more seasonally flooded (**Fig. 8**).

There is a strong spatial pattern in the distribution of wetland types across the Columbia Plateau. Wetlands in the Glaciated Region tended to be more permanently flooded, while wetlands in the Channeled Scablands tended to be more seasonal (**Fig. 8**). Following this pattern, wetlands in the Glaciated Region were primarily classified as groundwater driven while wetlands in the Channeled Scablands were more commonly classified as surface water driven. Surface water driven wetlands clearly tracked the high frequency variability associated with seasonal climate variability, which the VIC model reproduces (e.g. soil moisture layers, precipitation).

For groundwater driven wetlands, the variability in the reconstructed hydrographs was beyond that captured by simulated soil moisture dynamics on which the wetland-specific regression models were originally developed. However, the groundwater surrogates (CDFM and CDFM P-ET) that we calculated reproduced the multi-year climate variability for the reconstructed hydrodynamics, which indicated that these wetlands were likely driven by groundwater levels.

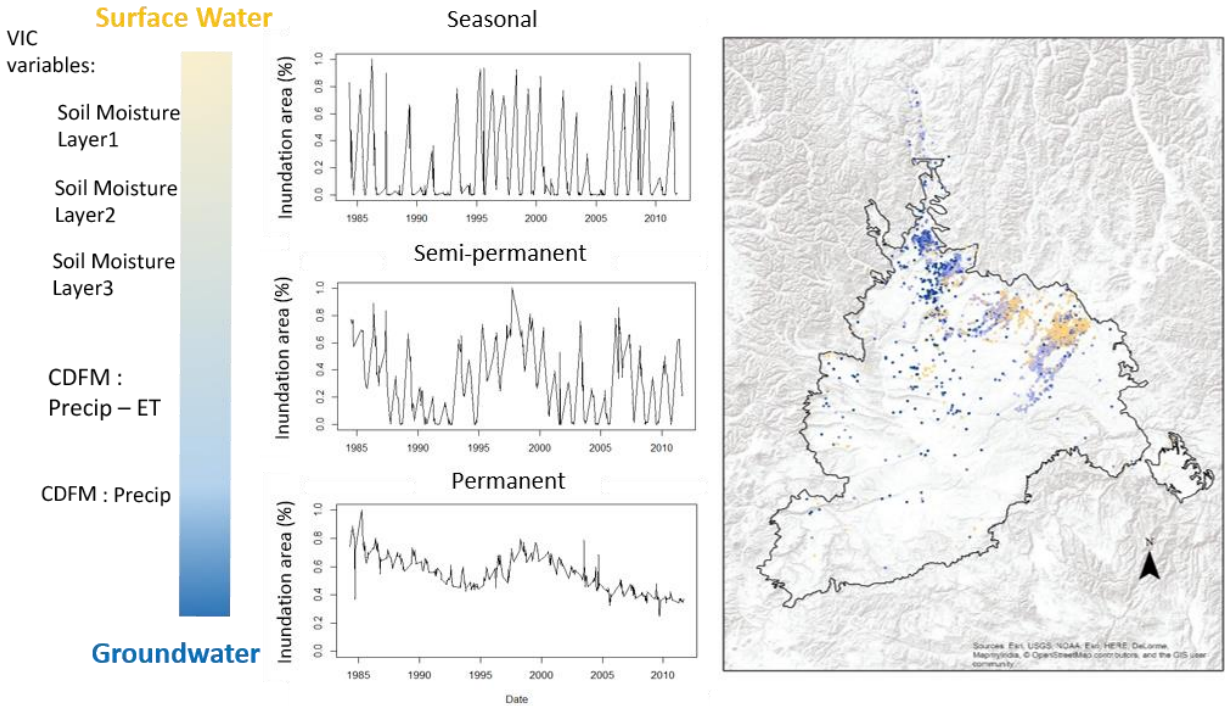


Figure 8. A diagram of the groundwater to surface water continuum and how it relates to: VIC variables (left), wetland hydrologic regimes (middle), and spatial distribution (right). Our wetland-specific regression models do not cover the full continuum, rather we used VIC variables that fell at discrete locations along this continuum.

Historical change

Since 1984, wetlands in the Glaciated Region of the Columbia Plateau have shown decreases in annual mean surface water area, while wetlands in the Channeled Scablands either have not had a dramatic change in annual mean surface water area, or have increased slightly (**Fig. 9**). This pattern is strongly related to the spatial distribution of groundwater driven and surface water driven wetlands described above. Groundwater driven wetlands have decreased in mean surface water area, while surface water driven wetlands have increased in mean surface water area or have had little change in mean surface water area.

Based on examination of long-term climate patterns the decrease in mean surface water area for groundwater driven wetlands was likely caused by a decrease in groundwater levels. More research is needed to explore the driving factors of this change. However, because groundwater driven wetlands deviate from climate patterns in these areas our analysis supports the hypothesis that groundwater extraction for human use is one possible cause of this observed decline.

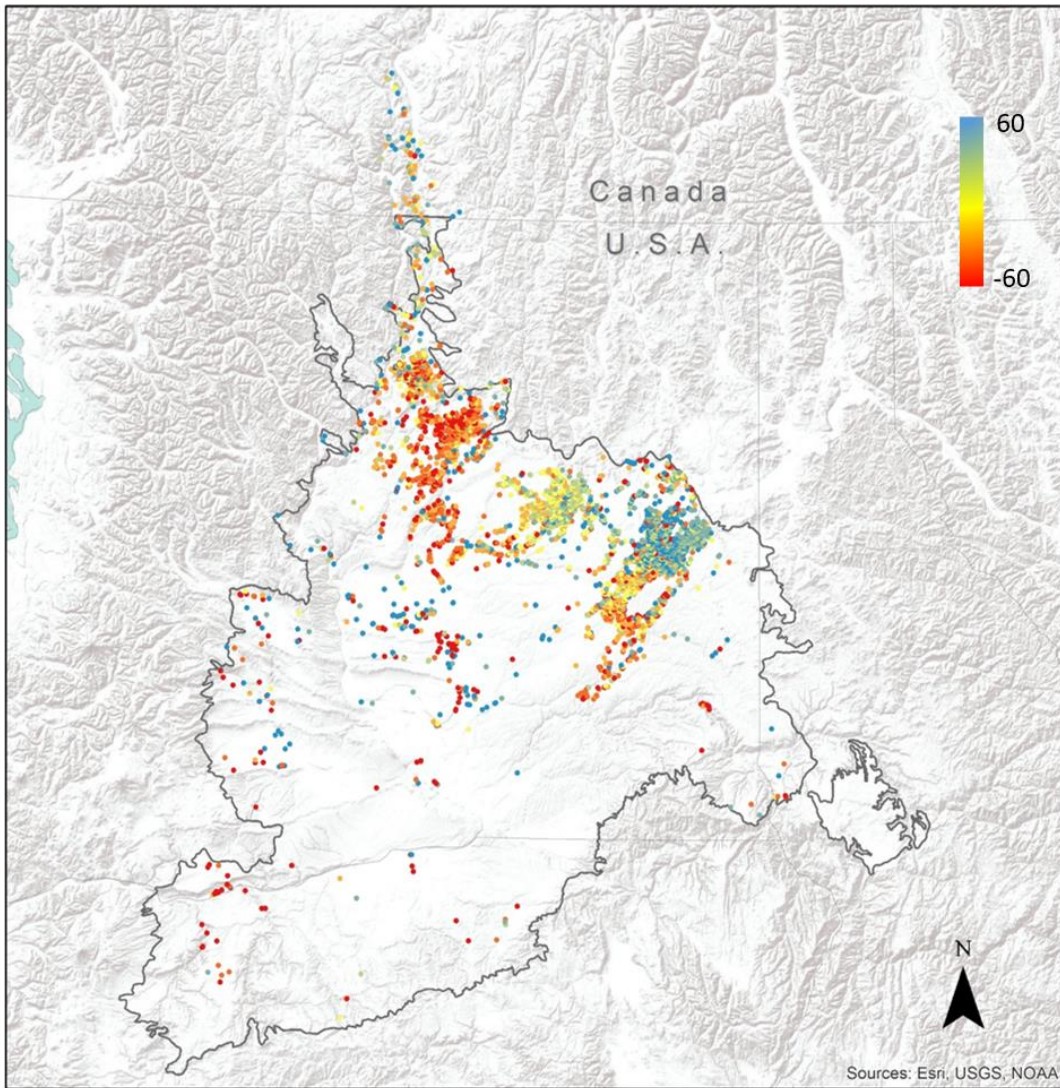


Figure 9. Change (slope of trendline) in mean surface water area for wetlands in the Columbia Plateau (1984 – 2011) using 5,382 wetlands hydrographs derived from remote sensing.

Climate change projections

Our selected climate change scenario predicts increases in winter precipitation and an increase in overall temperatures, by the end of the 21st century. Under this scenario, our analysis projected that different wetlands across the Columbia Plateau will have a different direction of change in annual maximum surface water area, drying frequency, and average drying date by the 2080s. The direction of change projected for a particular wetland is dependent on two factors: a wetland's primary hydrologic input and their location within the Columbia Plateau.

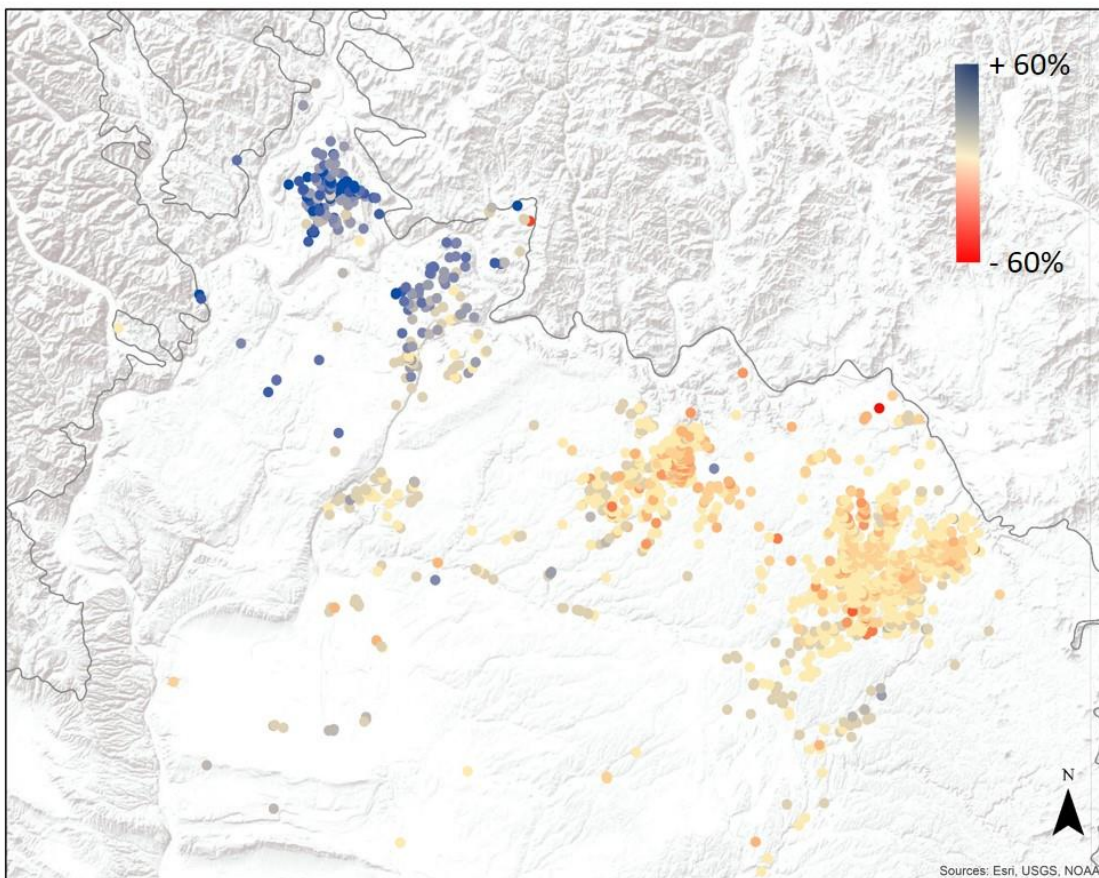


Figure 10. Projected changes in maximum annual surface area (%) for wetlands across the Columbia Plateau. Change projections were only modeled for the 1,735 wetlands with wetland-specific regression models with good fit, which were concentrated in the Glaciated Region and the Channeled Scablands.

In general, groundwater driven wetlands in the Glaciated Region are expected to show increases in annual maximum surface water area, to dry less frequently, and if they do dry out they will dry later in the season. Groundwater driven wetlands in the Channeled Scablands are expected to either see no change or to show decreases in annual maximum surface water area, to dry more frequently, or dry earlier in the season (**Fig. 14**). On the other hand, surface water driven wetlands are expected to either show no change or to get drier (**Fig. 18**). The degree of change is much greater for groundwater fed wetlands than for surface water driven wetlands.

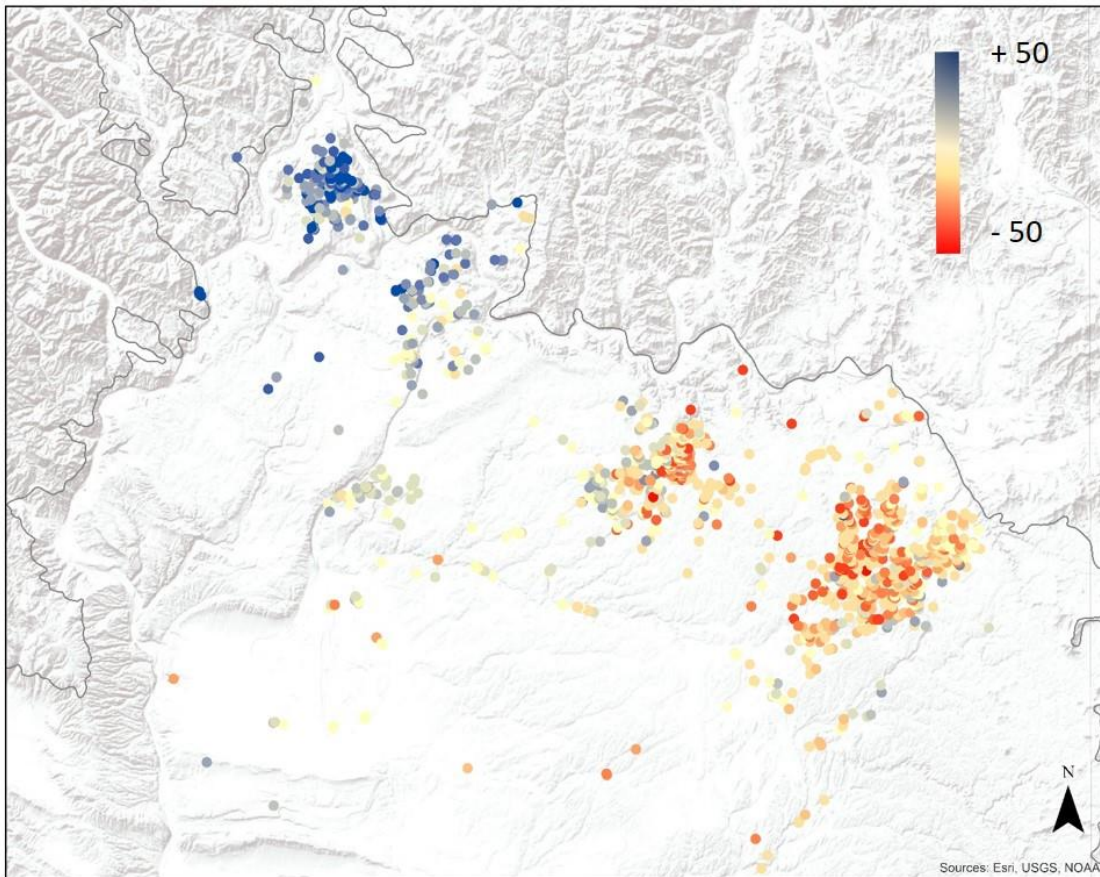


Figure 11. Projected changes in drying frequency for seasonal and semi-permanent wetlands for the 2080s. Metrics were not calculated for permanently flooded wetlands, as by definition permanently flooded wetlands do not dry out.

Groundwater driven wetlands such as those concentrated in the Glaciated Region are more sensitive to changes in precipitation, while wetlands in areas with less topographical complexity

(such as those found in the Channeled Scablands) are more likely to be driven by surface water inputs and are more sensitive to changes in temperature. Because each wetland has hydrologic inputs that vary through time, each wetland responds differently to changes in precipitation and temperature. This makes it hard to generalize results across the ecoregion. Some wetlands may not see substantial change because increases in precipitation offset the effects of increases in temperature and ET. For other wetlands, especially groundwater driven wetlands in the Channeled Scablands, winter precipitation increases will likely not be enough to offset the expected increases in temperature and ET. While we were unable to perfectly model the relationship to climate for each wetland, our results do provide an indication of where a particular wetland might fall on the continuum from surface water driven to groundwater driven. Therefore, even if a wetland had poor model fit it is still possible to infer how a wetland will likely respond to climate changes by examining the primary hydrologic drivers and expected change in the surrounding wetlands.

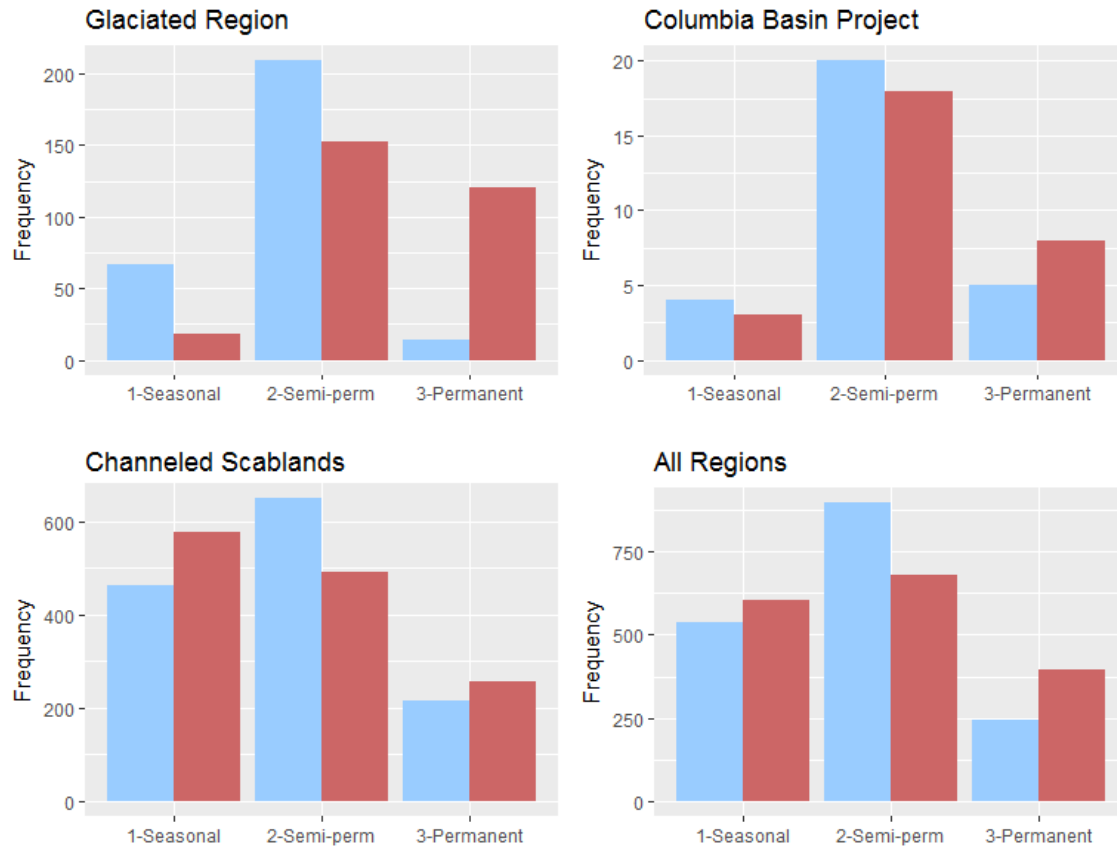


Figure 12: Change in distribution of wetland types from the 1980s (blue bars) to the 2080s (red bars) for the entire Columbia Plateau and broken out for each region. There is little change in wetland types across all Columbia Plateau. However, the Glaciated Region is expected to see a shift to more permanently flooded wetlands and the Channeled Scablands is expected to see a shift towards more seasonally flooded wetlands.

The Columbia Plateau is expected to see an overall shift in the distribution of wetland types, with fewer semi-permanently flooded wetlands and more seasonal and permanently flooded wetlands (**Fig. 12**). However, the change in wetland types will not be evenly distributed throughout the ecoregion. In the Glaciated Region, more wetlands are expected to shift to permanently flooded, leaving fewer semi-permanent and seasonal wetlands. On the other hand, in the Channeled Scablands, more wetlands are expected to shift toward being seasonally flooded, and a small increase in more permanently flooded wetlands is expected, leading to a decrease in the numbers of semi-permanently flooded wetlands. For the Columbia Basin Project area we projected a small shift toward more permanently flooded wetlands, although this trend is less certain, due to a

small number of wetlands in this region for which wetland-specific regression models fit well enough to allow us to estimate change. This lack of good-fit regression models is likely related to the following reasons:

- Wetlands in this region are connected to deeper groundwater sources, which the VIC model does not account for.
- Groundwater is influenced by the Columbia Basin Project itself and not solely by climate.
- Wetlands in this region have modified hydrology due to irrigation runoff, groundwater depletion or increases, and disturbance.

Groundwater driven wetlands

Our analysis showed that different wetlands are likely to show change in wetland surface water area in different directions. In general, groundwater driven wetlands in the Glaciated Region are expected to get wetter, while groundwater driven wetlands in the Channeled Scablands are expected to get drier or stay the same.

We projected that groundwater driven wetlands in the **Glaciated Region** will see:

- Increases in maximum annual surface water area (**Fig. 14**)
- Increases in minimum annual surface water area (not shown, as it is a similar pattern to maximum surface water area)
- Less frequent drying by the end of the season (**Fig. 15**)

We projected that groundwater driven wetlands in the **Channeled Scablands** will see:

- Decreases in maximum annual surface water area or have little change (**Fig. 14**)
- Decreases in minimum annual surface water area (not shown, as it is a similar pattern to maximum surface water area)
- More frequent drying, or see little change (**Fig. 15**)

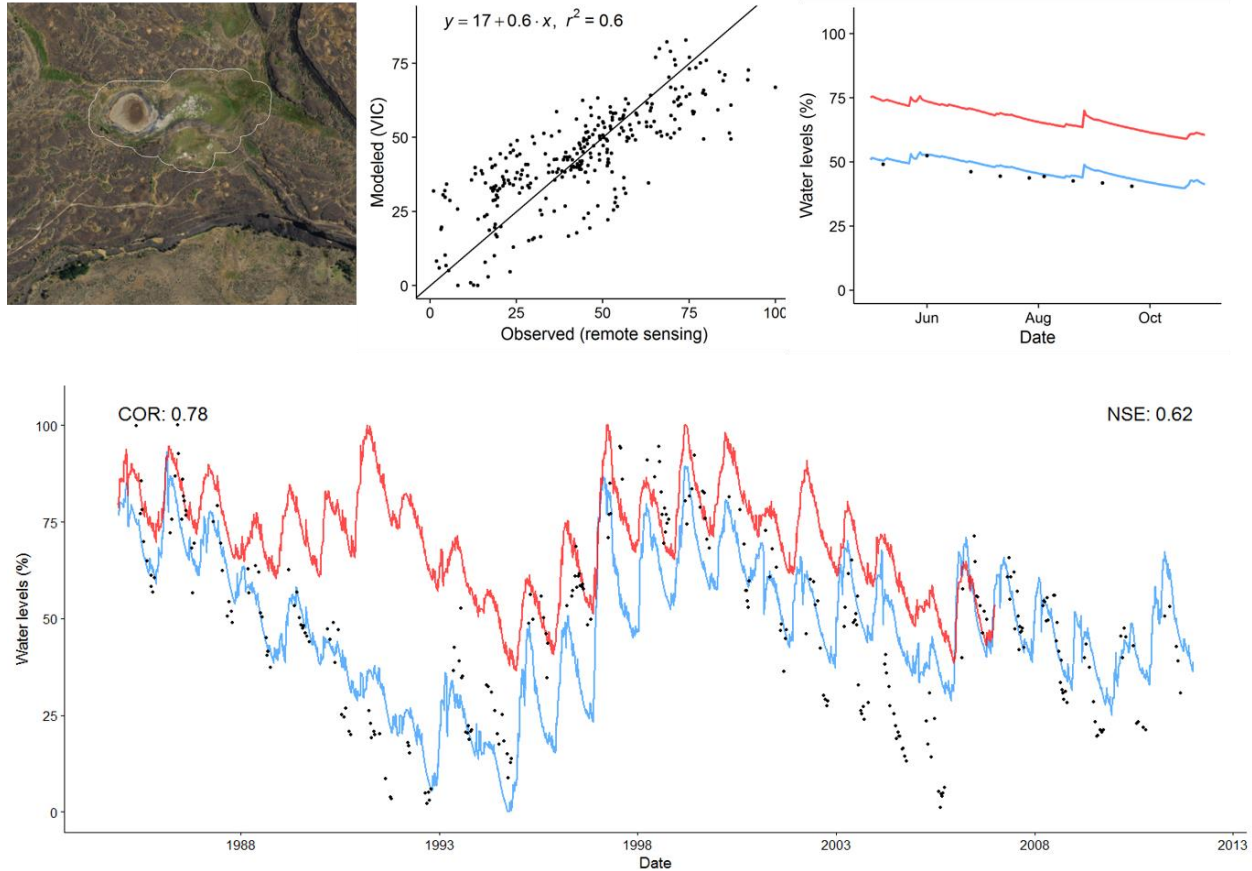


Figure 13. Example of results for a groundwater driven wetland in the Glaciated Region. Black dots represent surface water area as estimated using remote sensing methods. Blue lines represent the modeled hydrograph based on the wetland-specific regression model (hindcasting). Red lines represent the projected hydrograph for the 2080s (forecasting). The upper left panel shows an aerial photo of the wetland. The upper center panel shows the fit of this wetland’s regression model. The upper right panel shows average seasonal drawdown for the 1980s (blue) and 2080s (red). The lower panel shows the observed data, modeled hydrograph, and the projected hydrograph for the 2080s.

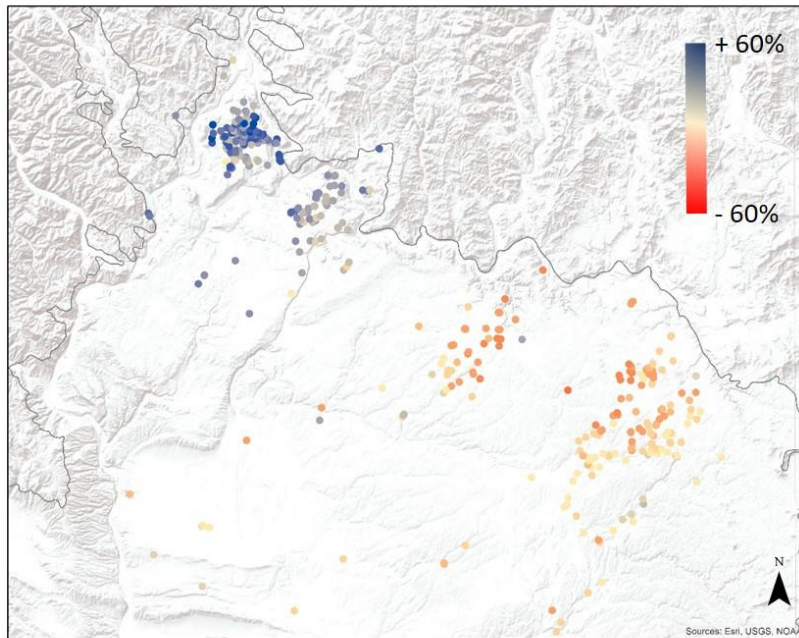


Figure 14. Projected changes in maximum annual surface area (%) for groundwater driven wetlands across the Columbia Plateau.

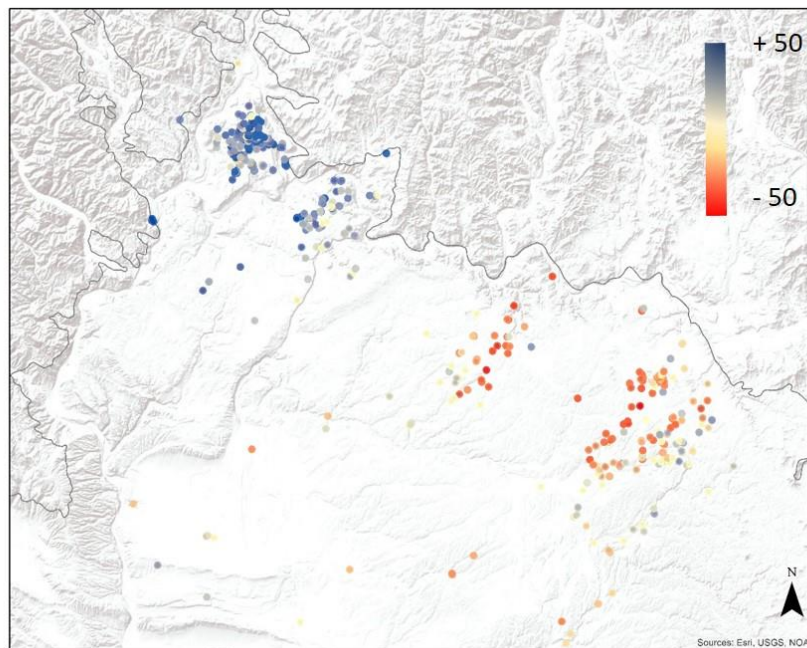


Figure 15. Projected changes drying frequency (number of years out of 100) for groundwater driven wetlands for the 2080s.

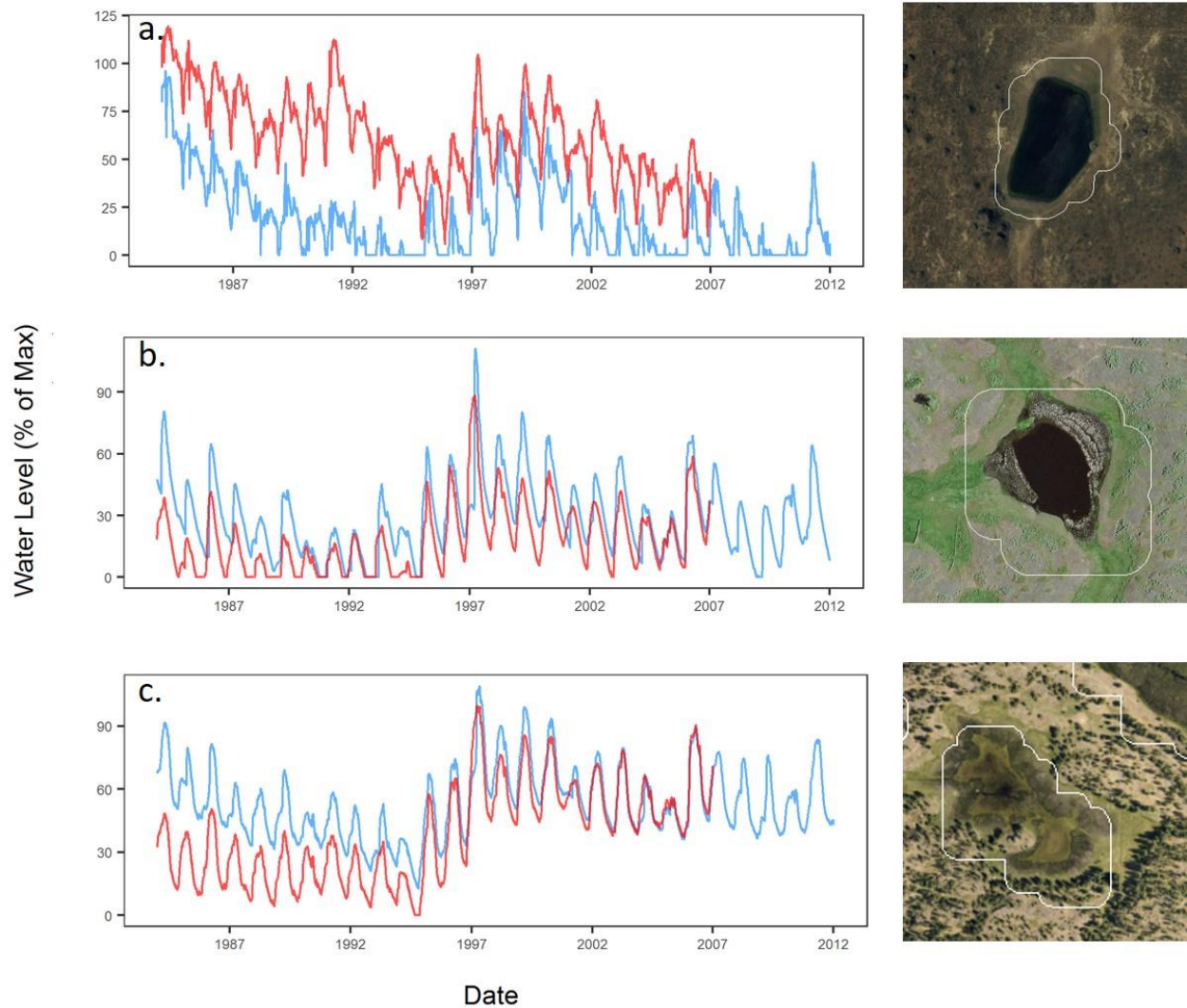


Figure 16. Historical (1980s, in blue) and future projected (2080s, in red) hydrographs for three groundwater driven wetlands in the Columbia Plateau located across the west to east gradient. Wetland in the top panel is located in the Glaciated Region, in Douglas County (a), wetland in the middle panel is located in the Channeled Scablands, near Swanson Lakes Wildlife Area, close to the Glaciated Region (b), and wetland in the bottom panel is located in the Channeled Scablands, near Turnbull Lakes National Wildlife Refuge (c). These wetlands are representative examples of the projected changes for groundwater driven wetlands across the ecoregion, from west (a) to east (c).

Surface water driven wetlands

Our analysis showed that surface water driven wetlands in the Columbia Plateau are expected to get drier or show little change. Most surface water driven wetlands are located in the Channeled Scablands.

We projected that surface water driven wetlands in the **Columbia Plateau** will see:

- Decreases in maximum annual surface water area, or see little change (**Fig. 18**)
- Decreases in minimum annual surface water area, or see little change (not shown, as it is a similar pattern to maximum surface water area)
- More frequent drying, or little change in drying frequency (**Fig. 19**)
- Drying later in the season, or little change in drying date (**Fig. 20**)

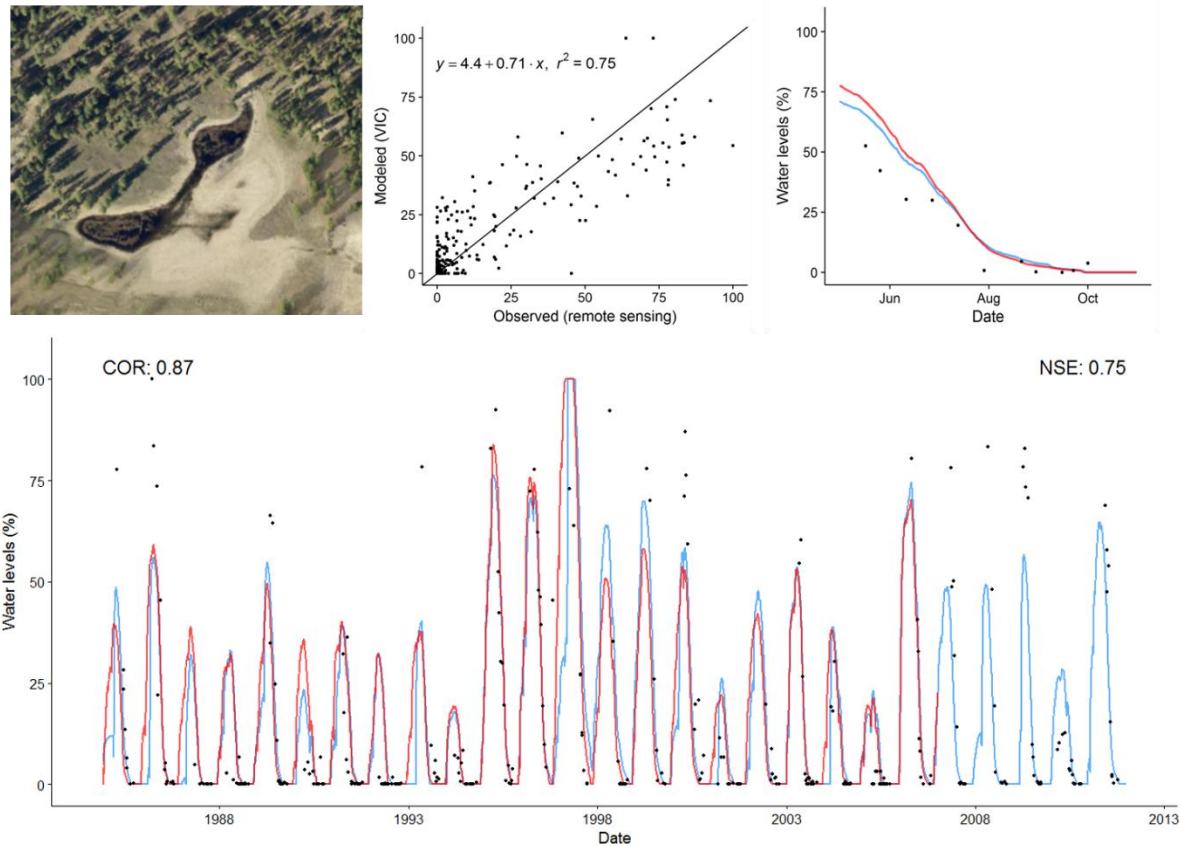


Figure 17. Example of results for a surface water driven wetland in the Channeled Scablands . Black dots represent surface water area as estimated using remote sensing methods. Blue lines represent the modeled hydrograph based on the wetland-specific regression model (hindcasting). Red lines represent the projected hydrograph for the 2080s (forecasting). The upper left hand panel shows an aerial photo of the wetland. The upper center panel shows the fit of this wetland’s regression model. The upper right hand panel shows average seasonal drawdown for the 1980s (blue) and 2080s (red). The lower panel shows the observed data, modeled hydrograph, and the projected hydrograph for the 2080s.

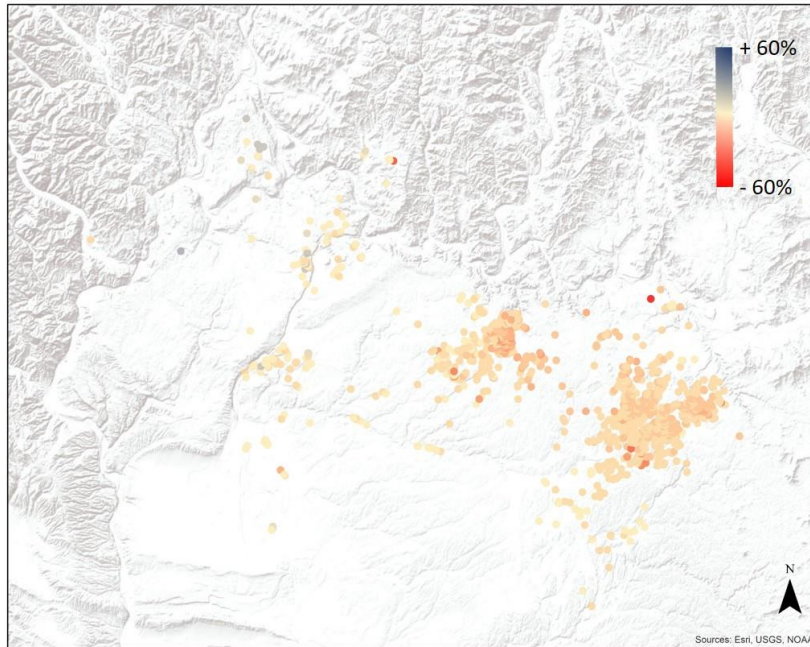


Figure 18. Projected changes in maximum annual surface area (%) for surface water driven wetlands across the Columbia Plateau.

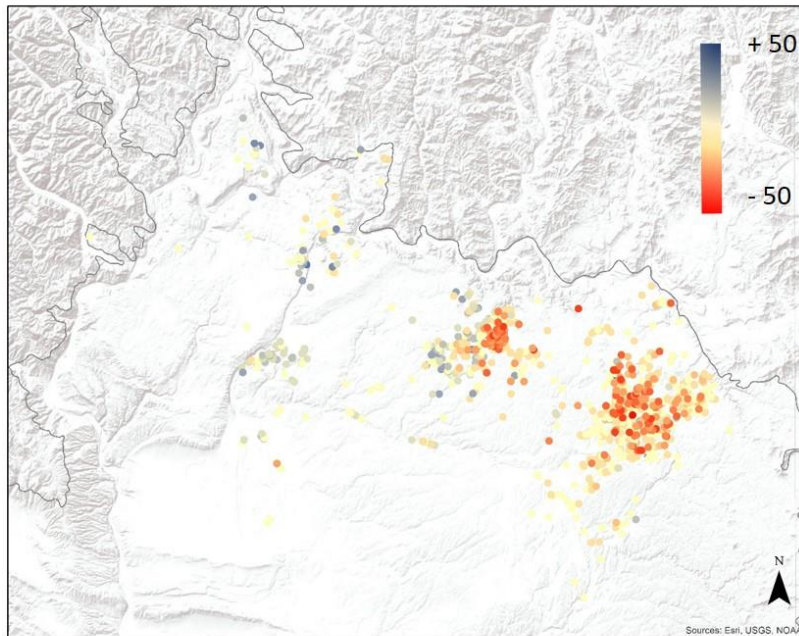


Figure 19. Projected changes drying frequency (number of years out of 100) for groundwater driven wetlands for the 2080s.

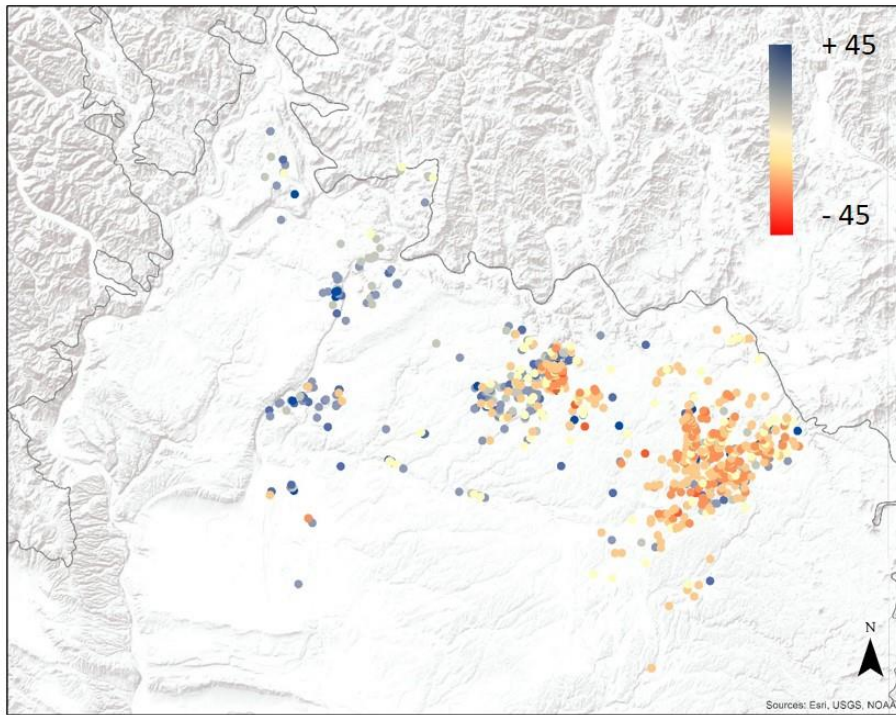


Figure 20. Projected changes in drying date (# of days) for surface water driven seasonal and semi-permanent wetlands for the 2080s. Metrics were not calculated for permanently flooded wetlands, as by definition permanently flooded wetlands do not dry out.

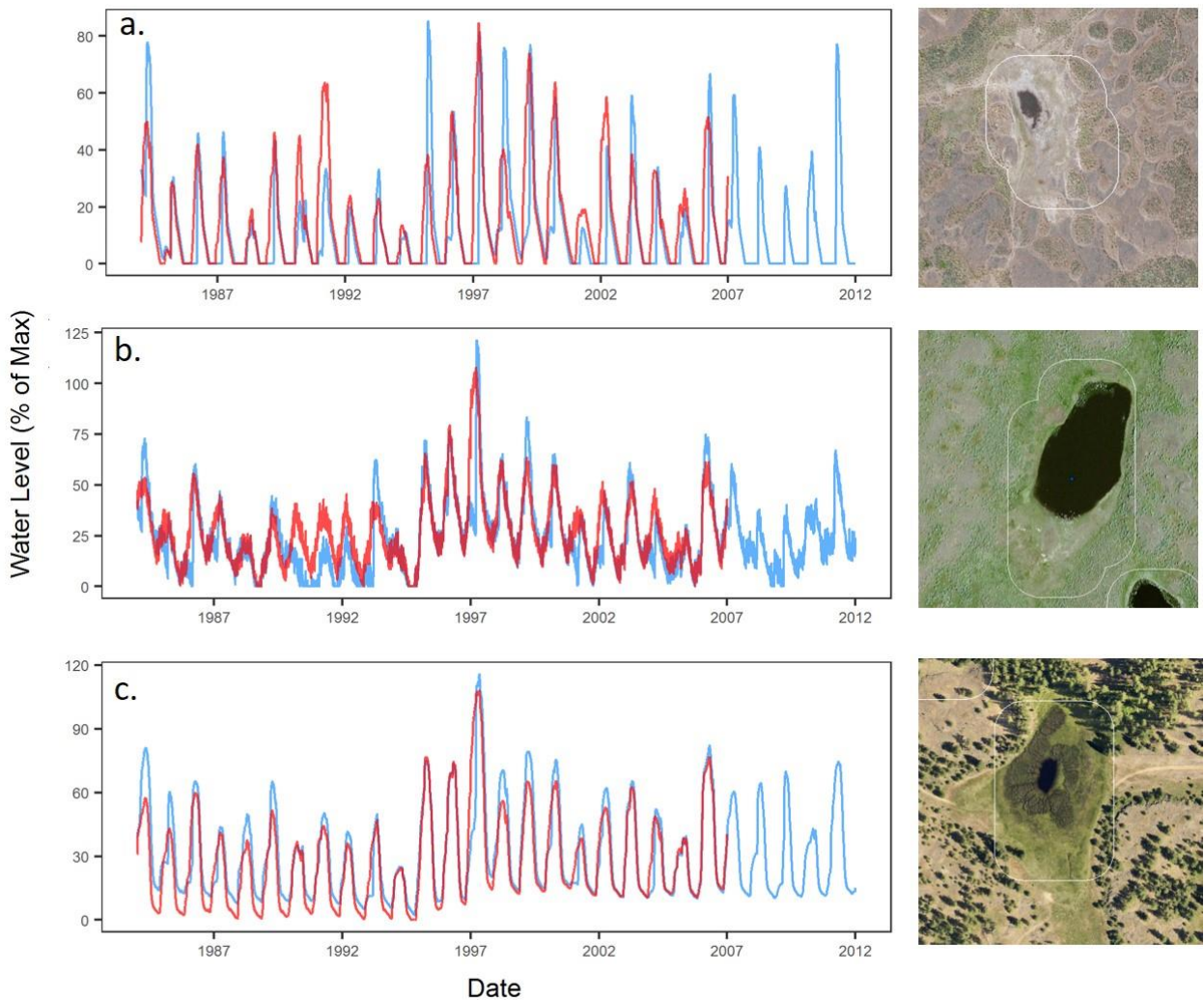


Figure 19. Historical (1980s, in blue) and future projected (2080s, in red) hydrographs for three surface water driven wetlands in the Columbia Plateau located across the west to east gradient. Wetland in the top panel is located in the Glaciated Region, in Douglas County (a), wetland in the middle panel is located in the Channeled Scablands, near Swanson Lakes Wildlife Area, close to the Glaciated Region (b), and wetland in the bottom panel is located in the Channeled Scablands, near Turnbull Lakes National Wildlife Refuge (c). These wetlands are representative examples of the projected changes for surface water driven wetlands across the ecoregion, from west (a) to east (c).

Using These Wetland Data

All of our products (wetland point and polygon locations, reconstructed and empirical datasets, future hydrographs under projected climate change, historical to future change metrics) can be used to explore both historical changes in wetland hydrology and potential future changes for a range of applications and to help managers develop long-term climate change adaptation strategies.

In order to apply these data, users should examine the results through the lens of their particular objectives (e.g. protecting migratory bird habitat, managing populations of tiger salamanders, or improving wetland hydrology), as climate change impacts will have different significance for different objectives. For example, increases in surface water area may be a net benefit for migratory birds as long as increases are not too large and do not occur at the wrong time of the year, which could potentially flood out their nests. Knowing the potential for this to happen could allow adaptation in those wetlands subject to regulation of water levels, by managing water levels to avoid extremes or to slow rates of increase, avoiding such flooding of surrounding nesting areas.

An Approach for Using These Data to Inform Management Decisions

We have worked closely throughout this project with managers, scientists, and policymakers to make this dataset both useful and used. As part of this collaboration, we shared this project's results, as well as providing guidance in a workshop setting on an approach to help decision-makers use these data to determine the climate change adaptation actions they need to take in order to achieve their specific wetland conservation or management objectives. This approach followed the steps developed by Beechie et al. (2013) for adapting actions in salmon recovery plans in light of a changing climate. It entails four main steps:

1. *Articulate your wetland management or restoration objectives.* We asked managers invited to the workshop to provide this information in a pre-workshop survey. A number of different objectives were identified, ranging from maintaining or restoring seasonal

hydrology or ecological function to restoring native vegetation or conveying the importance of wetlands.

2. *Identify key climate change impacts of concern for the wetland type and location you are planning for.* An ecoregion-wide evaluation in patterns of change in the hydrology of wetlands using the data developed in this project allowed us to identify five main negative impacts of climate change: increased drying frequency, earlier average drying date, decreased annual maximum and minimum water levels, and the drying of adjacent uplands. It is worth noting that changes in these variables were associated with drying of wetlands only in a portion of the ecoregion, mainly in the Channeled Scablands region. Users should focus on subsets of the data that best fit with their authorities and objectives.
3. *List management or restoration actions currently being implemented or considered to achieve your management objectives.* This was also part of the pre-workshop survey, and respondents identified a range of actions being considered. It was noteworthy that, though the objectives varied, the actions identified were fairly similar, and included: engineering project to manage water retention, planting native species and controlling non-native invasives, excluding grazing, protecting wetlands from various impacts through regulations, purchase, or voluntary agreements.
4. *Evaluate whether current actions are likely to ameliorate climate change impacts of concern.* There are multiple ways in which this evaluation can be approached, depending on the availability of information. Beechie et al. (2013) used a literature review. In the workshop setting, we relied primarily on expert opinion of participants. The questions raised through the expert discussion, however, could help guide further review of data or published information to determine which actions are most likely to ameliorate climate change impacts.

Organizing the resulting decisions into a matrix (see Table III in Beechie et al. 2013 for an example (Beechie et al 2013)) provides an easy-to-understand visual aid that synthesizes a large amount of information: objectives and actions in different rows, climate change impacts in different columns, and best understanding of each action's ability to ameliorate each impact in the body of the table. This structure will highlight actions that ameliorate multiple impacts,

actions that are unable to ameliorate any impacts, and impacts that are not addressed by current actions. Such highlights can help guide managers in decisions on which actions need to be continued, which need to be changed, and where additional, new actions might be needed to fully address climate change impacts.

Considerations for Appropriate Use of These Data

The dataset used for this analysis is freely available on the ScienceBase (www.sciencebase.gov). Users should be aware of the following key points regarding appropriate use of this wetland dataset.

- All of the data should be examined through the lens of the particular objective that one is trying to meet. As a first step one needs to understand how one's objectives (e.g. habitat, wildlife, ranching) are affected by the knowledge from the historical hydrographs, the modeled outcomes, and the climate change impact projections.
- These data provide information about historical patterns of flooding and drying, as well as projected climate change impacts to wetland hydrology for a particular wetland. While historical patterns can be evaluated to determine the possibility of direct human impacts (e.g. draining) it cannot tease apart cumulative impacts. That is, the data does not tell you what has driven the historical changes seen. The user must determine, using additional knowledge and data, what the primary stressors have been and are, and which are likely to have the most immediate impact on their particular objectives for the wetland.
- We could not accurately model wetlands everywhere for many reasons (human impacts, influence of deep groundwater, hard to map etc..). However, one should be able to draw inferences for a specific wetland based on the regression model outputs, the projected impacts on nearby wetlands, the surrounding land uses, and local site knowledge.

Additional Considerations

- Semi-arid wetlands may be naturally more resilient to climate change than wetlands in other landscapes as they have adapted to a cycle of drought and deluge. However, little is understood about how much stress they can handle, and associated tipping points beyond which they may not recover (Bliss and Zedler 1998).

- In human dominated landscapes water storage ability may be impacted if groundwater is pumped at a higher rate than it can be recharged. A hotter, drier summer may put additional pressure on groundwater sources to support irrigation. Unexpected consequences could result without proper planning and regulation of groundwater resources. However, if carefully monitored increases in groundwater recharge due to climate change may offset some of the current groundwater extraction.
- We found that most seasonal wetlands included in our analysis had significant variability in their drying date, drying early in some years and later in others, which was impacted by increases in temperature. Other studies have demonstrated that seasonal wetland change may not be linear (Carter Johnson et al 2016), as seasonal wetlands that dry out early in the season are less impacted by increases in summer temperatures.
- We selected one climate change scenario, ECHAM5 forced by the A1B scenario, which approximate the average climate conditions simulated by twenty GCMs for the Pacific Northwest. Thus, our selected scenario represents a moderate, realistic scenario for the Columbia Plateau.
- The role of wetlands will become increasingly important under wetter, warmer winters and hotter, drier summers, as wetlands provide water storage in the hotter months. Wetlands may therefore be able to mitigate some of the effects of temperature increases, to varying degrees, due to their ability to store water in winter and provide aquatic habitat in the summer months, which, in the absence of stream channels, the surrounding upland areas cannot effectively do.
- The uncertainty inherent in climate projections can impede the success of conservation strategies that do not take into consideration adaptive management practices. Monitoring of wetland systems is therefore an important feedback mechanism that will help to ensure effective management and restoration of wetlands in a rapidly changing environment (Lawler et al 2010).

Conclusions and Future Work

Our work demonstrates that climate change impacts to wetlands in the Columbia Plateau are highly variable and specific to each wetland, depending on its primary hydrologic input, its annual pattern of flooding and drying (or not), and its location on the landscape. This variability

exists primarily because wetlands occur on a gradient from those fed by surface water to those fed by groundwater. Their climate response is linked to where they fall on this continuum, and how changes in precipitation and temperature will influence their inflow and outflow of water. Groundwater driven wetlands have a lag response to climate, which may be longer than the lag captured with the CDFM and the CDFM P-ET. More complicated statistical models than those used in this project exist to examine this response to climate, but are challenging to execute for thousands of wetlands (Long 2015; van der Burg et al 2016). Future work will focus on the relationship between climate and groundwater. Additional areas of future study include investigating uncertainty by incorporating additional GCMs and exploring other climate change scenarios, as the ECHAM5 A1B used in this study represents one climate change scenario and is based on the average of 20 GCMs from CMIP3.

As the impacts of climate change amplify, understanding the consequences for wetland dynamics will be critical for their sustainable management and conservation, particularly in arid regions such as the Columbia Plateau Ecoregion. As such, consistent datasets become critical to assess regional trends in wetland dynamics over time, including changes in wetland function. These assessments are necessary to understanding the full picture of wetland dynamics, and to develop—and achieve—conservation goals beyond “no net loss.”

Thanks

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