Published in final edited form as:

Remote Sens Environ. 2017 May ; 193: 180–192. doi:10.1016/j.rse.2017.02.016.

Three decades of Landsat-derived spring surface water dynamics in an agricultural wetland mosaic; Implications for migratory shorebirds

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Abstract

Satellite measurements of surface water offer promise for understanding wetland habitat availability at broad spatial and temporal scales; reliable habitat is crucial for the persistence of migratory shorebirds that depend on wetland networks. We analyzed water extent dynamics within wetland habitats at a globally important shorebird stopover site for a 1983–2015 Landsat time series, and evaluated the effect of climate on water extent. A range of methods can detect open water from imagery, including supervised classification approaches and thresholds for spectral bands and indices. Thresholds provide a time advantage; however, there is no universally superior index, nor single best threshold for all instances. We used random forest to model the presence or absence of water from >6200 reference pixels, and derived an optimal water probability threshold for our study area using receiver operating characteristic curves. An optimized mid-infrared (1.5–1.7 μm) threshold identified open water in the Sacramento Valley of California at 30-m resolution with an average of 90% producer's accuracy, comparable to approaches that require more intensive user input. SLC-off Landsat 7 imagery was integrated by applying a customized interpolation that mapped water in missing data gaps with 99% user's accuracy. On average we detected open water on ~26000 ha (~3% of the study area) in early April at the peak of shorebird migration, while water extent increased five-fold after the migration rush. Over the last three decades, late March water extent declined by ~1300 ha per year, primarily due to changes in the extent and timing of agricultural flood-irrigation. Water within shorebird habitats was significantly associated with an index of water availability at the peak of migration. Our approach can be used to optimize thresholds for time series analysis and near-real-time mapping in other regions, and requires only marginally more time than generating a confusion matrix.

Keywords

Surface water; Inundation; Agriculture; Time series; Classification; Random forest; Receiver operating characteristic curve; Threshold

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1. Introduction

Freshwater resources provide benefits to human and natural communities ranging from water, food and habitat provision, to waste treatment and greenhouse gas regulation; yet these critical resources are limited to <1% of the Earth's surface. Despite this small areal extent, there are substantial gaps in our knowledge of the distribution and variability of terrestrial surface water resources over time (Alsdorf et al., 2007; Turpie et al., 2015). Freshwater is poorly monitored and managed across the globe, especially with regard to wetlands and water applied to agricultural lands (Alsdorf et al., 2007; Pimentel et al., 2004). Even in California, which has one of the most highly engineered and intensively managed water systems in the U.S., water rights in some areas represent 1000% of the surface water supply (Grantham and Viers, 2014; Jenkins et al., 2004). Recent pronounced droughts highlight the added complexity of management under climate change interacting with human-imposed water stress, particularly in arid regions with high rates of wetland conversion (Maggioni, 2015; Van Loon et al., 2016).

Over half of the 75 shorebird species in the Western Hemisphere are in decline (Brown et al., 2001), indicating that wetland networks are in peril. Most migratory shorebird species are entirely dependent on wetlands for food and rest during long-distance journeys in the spring and fall (Brown et al., 2001); many face dual threats of habitat loss and climate change (Davidson, 2014; Morrison et al., 2006). Under ongoing climate change, inland non-tidal wetlands are at increased risk from future drought severity, and they will increase in importance for migratory shorebirds when sea level rise reduces access to coastal wetlands (Galbraith et al., 2002; Werner et al., 2013). To safeguard migratory fly-ways into the future, improved understanding of long-term wetland extent and variability over large areas is needed, as well as insight into the capacity for these systems to tolerate changes in water availability (Dudgeon et al., 2005; Turpie et al., 2015).

Satellite remote sensing is key to understanding surface water resources and how they are responding to intensified appropriation and modification by humans (Alsdorf et al., 2007; Turpie et al., 2015). In recent years, several global inundation analyses have been released that have moved from static, coarse scale (>1 km) products (e.g., Bontemps et al., 2011; Lehner and Döll, 2004; Verpoorter et al., 2014) to more dynamic offerings, such as the Global Inundation Extent from Multi-Satellites (Fluet-Chouinard et al., 2015) and the MODIS water mask (Carroll et al. 2009). Studies of wetland dynamics at global scales have typically focused on relatively short time periods with coarse spatial resolution (e.g., Papa et al., 2010; Prigent et al., 2007; 25-km grid cells), and therefore have been unable to capture smaller wetland features, or account for longer term cyclical hydrologic variability.

Landsat Thematic Mapper imagery can be used to map open water at 30-m resolution (Alsdorf et al., 2007; Baker et al., 2006) appropriate for resolving smaller, shallow wetlands that provide important migratory shorebird habitat (Strum et al., 2013). There is great potential for tracking long-term surface water dynamics given Landsat's <16-day revisit period from 1983 to the present (e.g., Feng et al., 2016; Mueller et al., 2016; Tulbure et al., 2016). The presence and duration of flooding can be informative in lieu of more intensive field measurements (Elphick, 2008; Farmer and Parent, 1997; Reiter et al., 2015). For

example, these attributes influence invertebrate prey densities, which are challenging to measure precisely in situ over large areas (Batzer, 2013; Lee et al., 1999; Lyzenga et al., 2006). Landsat's historical timespan permits analysis of multiple El Niño cycles, which strongly influence the frequency and intensity of precipitation for many regions, including the western U.S. (Fiedl and Roe, 2011; Hurrell and Loon, 1997). An analysis of the spatiotemporal variability of surface water at migratory stopover sites is needed to better understand baseline habitat conditions, particularly in regions with extreme seasonal and interannual variability.

Various approaches to identify surface water based on satellite imagery have been developed. Unsupervised classification approaches have been the most common technique in the past for mapping wetlands (Ozesmi and Bauer, 2002). Of the many supervised classification methods available, maximum likelihood has been used most frequently (Mather, 1985; Ozesmi and Bauer, 2002), however classification trees have become increasingly popular, and typically produce superior results (Baker et al., 2006; Breiman, 2001; Friedl and Brodley, 1997; Tulbure and Broich, 2013). Thresholds can also be used for land cover mapping, with an advantage of lower overall investment for the user; once developed, a classification can be generated virtually instantaneously (Chuvieco, 2016; Friedl and Brodley, 1997). Thresholds can be identified from individual multi-spectral bands as well as water indices such as the normalized difference water index (NDWI; McFeeters, 1996), modified normalized difference water index (MNDWI; Xu, 2006), automated water extraction index (AWEI; Feyisa et al., 2014) and Tasseled Cap wetness index (Crist & Cicone, 1984).

These water indices have variable performance depending on scene conditions and study area extent (Fisher et al., 2016; Yang et al., 2015); thresholds also vary in time and space (Friedl and Brodley, 1997). Thorough comparisons of multiple indices have been limited to a handful of studies (Campos et al., 2012; Fisher et al., 2016; Ji et al., 2009) with no clear best index for global application. Previous research indicates that thresholds should be modified for local conditions (Feyisa et al., 2014; Xu, 2006), yet few studies provide guidance for appropriate threshold optimization methods. A recent study by Campos et al., 2012 used the mean and standard deviation of values across 12 monthly images to select a threshold, while others have used omission and commission error as the basis of threshold selection (Fisher et al., 2016; Yang et al., 2015). Sheng et al. (2016) used iterative segmentation to identify NDWI thresholds for mapping lakes in Oceania. Ji et al. (2009) used spectral unmixing of pure pixels derived in a lab setting to suggest default thresholds for different fractional water coverages (starting points for 25, 50, 75, 100% water cover). Some of these studies remain untested outside of lab conditions (Ji et al., 2009), while others incorporate more field validation points than is normally practical (Fisher et al., 2016). Most studies do not explicitly evaluate accuracy outside of the source regions and dates used to train water classifications (Campos et al., 2012; Feyisa et al., 2014; Fisher et al., 2016; Sheng et al., 2016), which is of particular import for time series analysis.

This study used the entire Landsat thematic mapper time series (1983–2015) to evaluate water distribution patterns during spring shorebird migration in the Sacramento Valley of California, a globally important wetland stopover (Western Hemisphere Shorebird Reserve

Network, 2009). Previously published water mapping work in this system over shorter timescales (<10 years) has employed Landsat in both unsupervised and supervised classifications (Reiter et al., 2015; Reiter and Liu, 2011; Spell et al., 1995). Classification and change detection procedures must be efficient if applied across an extensive time series, and retain a satisfactory level of accuracy. Our objectives were to: 1) develop a reproducible approach to optimize a threshold that accurately identifies open water from the Landsat surface reflectance time series, 2) compare this approach to other methods typically used in mapping water, and 3) assess spatial and temporal patterns of open water from the historical record to inform water and wetland management. Hereafter we use *water* to refer to areas where open water, unobscured by vegetation, was present and *non-water* to refer to regions where open water was not detected.

2. Data and methods

We first built a Landsat surface reflectance time series for cloud-free, non-urban areas from 1983 to 2015. We then tested different spectral and water index thresholds against supervised classification methods, and subsequently identified an overall spring water/non-water threshold using extensive reference data for validation. Finally, we applied the optimized spring threshold for classification of open water from the 32-year time series, and analyzed spatiotemporal patterns and climate sensitivity of water within important migratory shorebird habitat.

2.1. Study area

The Sacramento Valley, in the northern Central Valley of California, is predominantly an agricultural landscape, although highly managed herbaceous wetlands remain on federal, state, and private lands (USDA-NASS, 2014; Fig. 1). More than 90% of the historically occurring wetlands have been lost in the Central Valley (Frayser et al., 1989). The Sacramento Valley hosts 96% of California's flood-irrigated rice (~20% of U.S production, Central Valley Joint Venture, 2006; Strum et al., 2013), which serves as important surrogate habitat for shorebirds in areas with high wetland loss (Barbaree et al., 2015; Elphick, 2000, 2010). Despite extensive historical wetland loss, the Sacramento Valley is recognized by the Western Hemisphere Shorebird Reserve Network as a site of international importance (Western Hemisphere Shorebird Reserve Network, 2009). The valley provides habitat for over 400,000 shorebirds each spring, with the peak of migration typically occurring in April (Central Valley Joint Venture, 2006; Shuford et al., 1998).

Much of California's water is supplied by the snowpack in the Sierra Nevada mountains, which is projected to decrease in average volume and duration in the future (Cayan, 1996; Cayan et al., 2008). The Sacramento Valley receives an annual average of 890 mm of precipitation, with the majority of accumulation from late fall through early spring (NOAA National Centers for Environmental Information, 2016); however this varies with climate cycles. A total of 1488 mm of precipitation were recorded under strong El Niño conditions in 1998, while only 541 mm were recorded for 2014, the third driest year on record in the state. Local allocations and water application in the Central Valley are driven by water rights and policy decisions, as opposed to the natural patterns of water distribution and abundance

(Grantham and Viers, 2014). During spring, water used in the Sacramento Valley is primarily sourced from reservoirs that capture montane snowmelt and runoff, which is delivered to wetlands and agricultural fields hundreds of kilometers away through an extensive network of canals, pump stations and levees.

2.2. Analysis tools

We used the RStoolbox package in R to develop image classifications and for accuracy assessment (Leutner and Horning, 2016). ArcGIS 10.3 was used to generate validation datasets, and Python was used for image processing (ESRI, 2014). Modelling and statistical analysis were conducted in R using the following packages: ggplot2 (Wickham, 2009), dplyr (Wickham and Francois, 2015), rasterVis (Perpinan and Hijmans, 2016), randomForest (Liaw and Wiener, 2002), reshape2 (Wickham, 2007), ROCR (Sing et al., 2005), SDMTools (VanDerWal et al., 2014), and spatial.tools (Greenberg, 2014).

2.3. Landsat time series

We gathered all available Landsat surface reflectance data for the Sacramento Valley representing the spring migration period (February–May) from 1983 to 2015 (WRS-2 path/row 44/33). Surface reflectance data were downloaded from USGS/EROS (<https://espa.cr.usgs.gov/>); these images were calibrated using the LEDAPS algorithm (Landsat 4–5, 7; Masek et al., 2013), or the L8SR algorithm (Landsat 8; Vermote et al., 2016) and CFmask (Zhu and Woodcock, 2012). For the spring migration season from 1983 to 2015, we processed a total of 242 Landsat surface reflectance scenes from Landsat 4, 5, 7 and 8 (Fig. 2A). These scenes had a range of cloud cover (Fig. 2B), but only isolated portions of the study area were consistently affected (Fig. S1).

2.4. Comparison of methods to identify water vs. non-water

We tested multiple methods to identify water in the study area. We used supervised maximum likelihood and random forest approaches, as well as optimized and default thresholds for commonly used water indices. To compare across both binary classifications and multi-class approaches, we generated a polygon validation dataset from a May 4, 2008 Landsat 5 image acquired under clear atmospheric conditions, using synchronous Quickbird imagery as a reference. We delineated polygons representing five land cover categories: open water, forested, other green vegetation, dry vegetation, or barren/urban, also coding each polygon as water or non-water. The open water polygons that we digitized did not include edge vegetation, but these did incorporate a mix of shallow and deep water pixels. Training and testing points were sampled from the polygon regions using a two-stage method after Wegmann et al. (2015). First, we partitioned the polygon dataset such that approximately 70% of the polygons were used for model training and 30% for model testing, in order to maximize spatial independence. For model training, we randomly sampled 500 points drawn from each class of interest (either water/non-water or multiple land cover types) in the training polygon set, removing points drawn from duplicate cells. We assessed the final water/non-water classifications produced by each approach using independent confirmed water and non-water locations; 250 points in each class were sampled from the May 4, 2008 Quickbird polygon testing regions and filtered to remove duplicates.

Supervised maximum likelihood and random forest (10000 trees, mtry = 1) classifications were used to map five cover types: water (490 training points), forested (453 training points), other green vegetation (418 training points), dry vegetation (460 training points) and urban/barren (434 training points). For both supervised methods, the resulting five-class map was reclassified to produce a final map of water and non-water for comparison with binary mapping methods. All multiple-class classifications were completed using the RStoolbox package including the 30-m multi-spectral Landsat bands and the 10-m national elevation dataset (U.S. Geological Survey, 2015).

We developed optimized thresholds for mid-infrared surface reflectance, the MNDWI, and the AWEInsh (non-shadow version of the AWEI) using a random forest model approach (Breiman, 2001) and receiver operating characteristic (ROC) curve analysis (Fawcett, 2006). A random forest model for water/non-water was built from the band or index values associated with randomly selected training points (~500 each for water and non-water). We identified an optimal threshold value using ROC analysis to determine the probability of membership in the water class that maximized the true positive rate and minimized the false positive rate (Greiner et al., 2000). The image was then reclassified using the optimized threshold to generate a water/non-water classification. To assess the utility of threshold optimization, we also produced classifications using the default thresholds proposed for the MNDWI (Xu, 2006) and the AWEInsh (Feyisa et al., 2014).

2.5. Optimized water/non-water threshold development

We assembled ground data as close in time as possible to Landsat image acquisition dates, including high-resolution (0.46–2.5-m) imagery and field observations confirming water or non-water presence on the ground from January to May for multiple years (Table 1). We identified obvious water and non-water point locations from high-resolution images. Field data consisted of landscape photographs of the Sacramento Valley collected as part of a separate study (Barbaree et al., 2016); fixed-wing aircraft were used to collect these photos during clear weather at altitudes of 600–800 m, with a final resolution of 75–150dpi. Reference datasets were subsequently built from these photos by manually classifying XY coordinates as water or non-water using high-resolution Google Earth imagery. We excluded reference data sources collected >10 days before or after a low-cloud cover Landsat overpass date, leaving a total of 12 reference datasets corresponding with images from Landsat 5, 7 and 8 from 2006 to 2014 (Table 1). Due to the lack of available February reference data, we included reference data from January to represent a more comprehensive range of potential spring conditions in our study area (Table 1).

To identify a single threshold for separating water/non-water in spring, we incorporated mid-infrared surface reflectance values from confirmed water/non-water reference locations (Table 1). We conducted a 9-fold random forest model cross validation, withholding 3 of the 12 dates from each model training set to maximize independence and rigorously assess predictive power. We identified an optimized spring water mapping threshold for our study area based on the probability of membership in the water class that maximized the true positive rate and minimized the false positive rate for the model average. To evaluate

performance, we examined confusion matrices and the area under the curve (AUC) generated from cross validation of random forest model runs (Bradley, 1997).

2.6. Time series image processing

We applied the optimized spring mid-infrared threshold for classification of the entire time series for the months of February, March, April and May from 1983 to 2015. We limited our analysis to low-elevation, non-urban land cover unaffected by clouds and cloud shadows. Cloud and shadow-free pixels were identified using the CFmask band (Zhu and Woodcock, 2012). We excluded areas mapped as 'developed' by the most recent USDA Cropland Data Layer (USDA-NASS, 2014) as well as higher elevation areas of mountainous terrain outside of the current Central Valley Joint Venture planning area, which is based on topography and watersheds (Central Valley Joint Venture, 2006).

Analyzing the full 1983–2015 time series necessitated the use of SLC-off Landsat 7 images, which are missing approximately 22% of data, even under cloud-free conditions. To address this challenge, we developed a unique interpolation approach to infer water presence in the areas of missing data. Much of the landscape has little elevation variation and is subject to artificial flooding; therefore, we applied an inverse distance weighted (IDW) interpolation to threshold classifications, using county land use survey lines collected from 1994 to 2011 as boundaries (California Department of Water Resources, 2016b; Fig. 3). We also applied an IDW interpolation to the CFmask to fill cloud and shadow regions in missing data areas (Zhu and Woodcock, 2012). The accuracy of the IDW interpolation was assessed for a cloud-free Landsat 7 image acquired on March 10, 2014, using a WorldView2 image collected on the same date.

2.7. Spatiotemporal analysis of shorebird habitat

We analyzed long-term trends of water extent and frequency in the Sacramento Valley within the most important habitats for shorebirds: flooded agriculture and herbaceous wetlands (Central Valley Joint Venture, 2006). For each Landsat image, we calculated the proportion of water detected in the cloud-free portions of the image and estimated total water extent, in addition to water extent in each habitat type based on the most recent National Land Cover Database (Homer et al., 2015). For each two-week period in spring from 1983 to 2015, we computed mean water extent, weighting observations by the proportion of cloud-free pixels in each image. To assess long-term trends in water availability, we applied linear regression for mean water extent estimates over time within each habitat type. Within-season variability was assessed with the mean water extent and variance for each two-week period in spring; we pooled observations from all years and weighted observations by the proportion of cloud-free pixels. We also calculated water frequency for each 30-m pixel by summing the total detections of water presence, corrected for the total number of cloud-free instances.

Lastly, we explored the influence of interannual climatic variability on water extent. The California Department of Water Resources reports an annual Water Year Index for the Sacramento Valley based on the volume of total runoff in the river basin, which provides a continuous measure of climate variation (California Department of Water Resources,

2016a). This index is used to classify each water year (ending in September) as ‘Critical’, ‘Dry’, ‘Below Normal’, ‘Above Normal’ or ‘Wet’. We used linear regression to assess the relationship between the Water Year Index and water extent for each two-week period from 1983 to 2015.

3. Results

3.1. Comparison of methods to identify water vs. non-water

We compared multiple methods to map water in the study area (Table 2, Fig. S2); for the thresholds, we compared the underlying random forest models and ROC analysis results (Table S1) in addition to the accuracy of the final threshold classifications (Table 2). Supervised classifications mapped water with high accuracy (user’s and producer’s accuracy >98%; Table 2, Fig. S2). Of the threshold methods, the optimized mid-infrared reflectance threshold achieved the highest overall accuracy (Table 2). Default thresholds for the water indices had lower user’s accuracy for the water class than optimized thresholds developed for each index; the default AWEInsh threshold was the only method to have a user’s accuracy <80%.

3.2. Evaluation of optimized spring water/non-water mid-infrared threshold

We identified a single mid-infrared threshold to map water/non-water in spring across multiple years with nine-fold cross-validation and ROC curve analysis of water/non-water random forest models (Table 3, Fig. 4). The optimal threshold for the model average that maximized the true positive rate and minimized the false positive rate occurred at a probability of 0.76 for membership in the water class (Fig. 4). This corresponded with a mid-infrared (1.5–1.7 μm) surface reflectance value of 0.069, which was determined to be the optimal threshold for separating water vs. non-water across the spring image time series in our study area. Applying the spring threshold and masking steps to achieve a final classification required approximately 20 min per image in a parallelized R workflow on a computer with an i7 processor and 16GB of RAM.

We assessed accuracy of the optimized mid-infrared threshold classification across the time series using both estimates reported by associated random forest models and ROC curve analysis results (Table 3, Fig. 4). Random forest models use bagging to build trees with bootstrapped resampling of the training dataset, such that each tree can be tested on the out-of-bag training samples not used in building that tree (Breiman, 2001). For our 9-fold cross-validation of random forest models, the average out-of-bag error rate was 9.5%, with an average of 11% error for the water class (Table 3). The non-water class had a lower average error rate, but a higher coefficient of variation than the error rate for the water class. ROC curve analysis produced accuracy estimates and an AUC for each model. The AUC measure combines the true positive rate and the false positive rate for the full range of probabilities of membership in the water class, where values closer to 1 represent a better classifier (Bradley, 1997). The average overall threshold accuracy reported by the ROC curve analysis across models was 92% and the average AUC across models was 0.94, indicating very good performance for a variety of dates and environmental conditions (Table 3, Fig. 4).

3.3. Effectiveness of IDW interpolation for SLC-off Landsat 7 classifications

We classified water in missing data regions with high accuracy using the spring threshold and an IDW interpolation constrained by county land use survey boundaries (Fig. 3). We achieved a user's accuracy of 99% (producer's = 98%) for the March 10, 2014 Landsat 7 image with 213 water locations and 188 non-water locations verified using World-view 2 imagery acquired on the March 15, 2014 (Table 1). Interpolation of water/non-water and the cloud and shadow mask added substantially to processing time, with up to 3.5 h required to process SLC-off Landsat 7 images (>10 times the time needed to process other images).

3.4. Landsat-derived spring open water dynamics

Over the study period 1983–2015, there was considerable variation in the estimated extent of open water in the Sacramento Valley over time (Fig. 5). The average water extent in the valley across the entire study period was ~75000 ha, with a standard deviation of nearly 56000 ha; both estimates were weighted by the cloud-free proportion of the study area for each observation. Our highest confidence estimate of maximum extent occurred on February 19th, 2004 when open water was detected on nearly 215000 ha (27% of the study area), with a cloud-free view of 99% of the study area. Although the 2004 water year was ranked as having 'Below Normal' precipitation (California Department of Water Resources, 2016a), above average precipitation occurred that February (Daly et al., 2008). After multiple years of recent drought a spring minimum extent of ~16500 ha (~2% of the study area; 96% clear view) was observed on March 21, 2015, slightly greater than the highest confidence minimum of ~13000 ha (<2% of the study area; 99% clear view) detected on April 11, 1988. We assessed interannual variability by conducting linear regressions of the mean estimated water extent for each 2-week period from 1983 to 2015 (Fig. 5). Over the study period, water extent declined by an average of 1300 ha per year in late March (adj. $R^2 = 0.22$, $p = 0.03$), and increased by an average of 1560 ha per year in late May (adj. $R^2 = 0.22$, $p = 0.006$).

Water extent also varied substantially within the spring season, mainly due to water management on agricultural lands (Fig. 6, Table S2). The minimum flood extent consistently occurred in April (peak migration), due to a limited extent of flooded agriculture. In early April a weighted average of ~26000 ha (~3% of the study area) ± 32000 ha of open water was present in the Sacramento Valley (Fig. 6), whereas average extent increased by a factor of five by late May. Natural and managed wetlands were also subject to substantial within season variation; however herbaceous wetlands exhibited a different seasonal pattern from agricultural lands. Year to year, water extent within herbaceous wetlands consistently decreased beginning in March; the minimum herbaceous wetland water extent typically occurred in May (Fig. 6).

From 1983 to 2015 strong within season variation in spatial water frequency patterns across the landscape was detected from our pixel-level analysis (Fig. 7, Fig. 8), revealing striking differences between months. Similar to the pattern of water extent, the frequency of water presence across the landscape was lowest in April. Higher water frequency was observed in February and May, although the spatial patterns differed in these months. In February, high water frequency areas were more spatially concentrated, and included riparian areas,

reservoirs and herbaceous wetlands as well as agriculture. In contrast, during May a broader swath of the landscape showed moderate water frequency due to the widespread presence of active flood-irrigated agriculture operations.

Notable differences in the water frequency within each habitat type were observed from 1983 to 2015 (Fig. 8). During peak shorebird migration, water was detected in <10% of the cloud free views for 80% of the agricultural land in the study area, while the highest water frequency in agriculture was observed in May. Water was detected more reliably in herbaceous wetland habitat during spring, particularly on federal and state-managed lands. Herbaceous wetland water frequency was typically highest in March, becoming less reliable as the spring season progressed.

We evaluated the effect of climatic variation on water extent in each habitat type over the study period using the California Department of Water Resources' Water Year Index, which measures overall water availability in the Sacramento River Basin based on streamflow for each water year (Fig. 9). The Water Year Index was a significant, but weak, predictor of mean water extent on agricultural lands in March and April. For herbaceous wetlands, the Water Year Index was a stronger predictor of water extent, and the relationship was significant for all spring months. Results suggest that water presence in shorebird habitats is most sensitive to climate in March and April.

4. Discussion

We measured water extent in the Sacramento Valley during spring for a time series spanning more than three decades. We determined that using an optimized spring mid-infrared threshold would expedite time series classification, while retaining high accuracy (Table 2, Fig. 4, Fig. S2). We incorporated 63 SLC-off Landsat 7 images in the time series, using an interpolation technique to accurately infer the presence of water in missing data regions. Although this data processing was time intensive, it was crucial for continuity between the loss of Landsat 5 and the launch of Landsat 8, and to increase the number of cloud-free observations of our study area. For a long time series where processing of many images is necessary, our approach provided relatively efficient and accurate estimates of water extent (Table 2). Any supervised classification method would have required substantially more time to develop and refine training data.

This work highlights the potential for threshold methods to estimate water extent over time with high accuracy. A limited number of studies have explicitly compared different water indices (Campos et al., 2012; Fisher et al., 2016; Ji et al., 2009; Yang et al., 2015), and fewer have compared these methods against supervised classification approaches. For analysis of only a few image dates, higher accuracy could likely be achieved with supervised classification methods, but this becomes overly time intensive for analysis of dense image stacks. The optimized threshold performed comparably to supervised classification methods that require substantial user input (Table 2, Fig. 4). However, a single global water index may not work well in all situations (Fisher et al., 2016; Yang et al., 2015). To take just one example, although the AWEI is widely recognized as having relatively low threshold variability (Feyisa et al., 2014), its success for different ecosystems was demonstrated for

just five Landsat image locations. Yang et al. (2015) noted that other indices sometimes outperformed AWEI in some regions, as we found in this study (Table 2).

Only a limited number of previous studies provide methods to optimize thresholds for spectral bands and water indices to local conditions (Campos et al., 2012; Fisher et al., 2016; Ji et al., 2009; Sheng et al., 2016; Yang et al., 2015). If reference data are already available for accuracy assessment, an optimized threshold can be developed in a matter of minutes in a reproducible fashion, as we have demonstrated here with random forest models and ROC curves. Other statistical optimization techniques could also be investigated such as a recent modification of Otsu's method, which maximizes between-class variance, without biasing the threshold to the land cover category with larger within-class variance. (Otsu, 1979; Xu et al., 2011).

Identifying a global water identification threshold is an attractive concept; however, we suspect that optimized thresholds will be more effective at local and regional scales, or within ecotypes. Fisher et al. (2016) developed a single threshold for a large area in Eastern Australia; however, this required hundreds of thousands of training points, which is not a practical undertaking in most cases. Furthermore, the authors did not explicitly test the accuracy of their single threshold outside of the training source areas. It makes perfect sense to use thresholds from the literature as a starting point for analysis; however, if reference data are available, we propose that researchers should tailor thresholds to their study area and period.

Tracking water trends over 32 years revealed important information about shorebird habitat dynamics in the Sacramento Valley. Our finding that the minimum water extent occurs during the peak of spring shore-bird migration (Figs. 6, 7) corroborates other studies (Barbaree et al., 2015; Central Valley Joint Venture, 2006) and stresses the need for conservation and management actions focused on this particular window of time. The decline in March water extent that we quantified gives further credence to concern that the Sacramento Valley may not provide sufficient habitat for migrating shorebirds, particularly during drought conditions (Central Valley Joint Venture, 2006). Water allocation decisions and the timing of flooding and drawdown of wetlands and agricultural fields have a strong influence on habitat and food availability; these factors therefore affect shorebird abundance and residence time in the valley. Non-linear spring water fluctuations (Figs. 5–9, Table S2) reflect practices in flood-irrigated rice fields, contrasting from fall migration in recent years where water extent consistently increased from September through December (Reiter et al., 2015). Managed wet-lands in the Sacramento Valley provide an important source of stable habitat for shorebirds; when agricultural water reaches its spring minimum extent, managed wetlands provide a comparable amount of core open water habitat. Consistent late winter and spring water habitats, such as that provided by the National Wildlife Refuge System and State Wildlife Management Areas, are especially crucial in years when agricultural flooding is delayed, or reduced due to water allocation restrictions.

Our findings have implications for wetland management under a changing climate. Water extent within both herbaceous wetlands and flood-irrigated agriculture was significantly correlated with the California Department of Water Resources' Water Year Index. While

agricultural water extent was less sensitive to fluctuations in water availability, it will be affected by climate change and emerging water policy. Precipitation in the Sierra Nevada is projected to decrease, particularly the amount and duration of the winter snowpack (Cayan et al., 2008), which is the main source of surface water in warmer, drier spring and summer months. In 2015, the state water project delivered just one-fifth of the water requested by users and a zero allocation was issued by the federal water project (“Watering California’s Farms”, 2015). Although farmers have historically pumped groundwater to supplement limited surface water supplies, particularly in years with low precipitation, legislation to regulate groundwater pumping recently passed in California (Sustainable Groundwater Management Act, 2014). Continued water deficits have heightened scrutiny of all forms of water use, and agriculture has been a popular target; rice production in 2014 was down 25% compared to the previous year, and there is increasing pressure for growers to reduce water use through drip irrigation (“Watering California’s Farms”, 2015). A move away from flood irrigation over large areas could provide substantial water savings, however it would also dramatically change shorebird habitat in the Sacramento Valley and other stopovers where extensive flood irrigation is currently practiced. Such changes in water management could result in reduced yields, shifts in the types of crops cultivated, and add strain on the livelihoods of the farmers that produce food for domestic and foreign consumers.

Our analysis faced some limitations. The Sacramento Valley was frequently affected by fog or cloud cover, particularly during El Niño conditions, and although Landsat’s overpass interval increased with the launch of Landsat 7, a substantial portion of available data comprised SLC-off imagery (Fig. 2). In addition to Landsat data limitations, high-resolution imagery and other reference datasets were not available for earlier years. As for observation frequency, it is possible that some agricultural fields may transition from flooded to drained within four days (unpublished results), in contrast to Landsat’s current 8-day overpass interval. This is unique to agricultural fields, as opposed to wetlands which draw down more gradually, and can affect collection of data to validate water presence and other characteristics of interest (Turpie et al., 2015). Water features may also be subject to confusion with topography and urban development; fortunately, our study area included low-elevation water features in rural areas. Estimates of water extent likely underestimated habitat availability, for example in moist soil at field edges and in areas obscured by dense emergent vegetation. Saturated area could be estimated from our water/non-water classification products by calculating the total length of water perimeters detected in the landscape.

Multiple stakeholders in California are recognizing the value of Landsat-derived water extent maps for management decisions. Our technique could expedite near real time mapping and monitoring efforts to inform policymakers in California, and in other regions experiencing water stress. Given access to sufficient training data, our approach could be modified and extended in order to meet the needs of research questions in other seasons, or other regions. The increased availability of high-resolution reference images such as the National Agricultural Imagery Program (U.S. Department of Agriculture Farm Services Agency, 2016) and Google Earth offer promising data sources that can be harnessed for threshold optimization in future studies of water dynamics.

5. Conclusions

In this study, we mapped open water from a 32-year Landsat time series using an optimized mid-infrared reflectance threshold. Thresholds that were optimized using random forest models and ROC curve analysis produced water classifications with higher user's accuracy than classifications using thresholds from the literature. Despite the irregularity of data availability and cloud cover, we were able to gather sufficient data from Landsat's extensive record to accomplish an analysis of long-term water extent trends within important habitats for migratory shorebirds. Interpolated classifications of Landsat 7 imagery provided a valuable data source for tracking water dynamics when other cloud-free images were not available. Our analysis revealed strong effects of climate and land management on the extent of water in Sacramento Valley wetlands and flood-irrigated agriculture. Water extent has been most limited at the peak of migration, when shorebirds urgently need flooded habitat for resting and foraging. Quantified reductions in March water extent also indicate that the amount of habitat leading into peak migration is dwindling. This study demonstrates the value for water and habitat management that can be drawn from analyzing an extended remotely-sensed time series. Additionally, adaptation of the reproducible threshold optimization demonstrated here can yield efficient high accuracy classifications of water in other regions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

Schaffer-Smith's work was supported by a NASA Earth and Space Science Fellowship (NNX13AQ15H) and an NSF DDRI Award (1459226). DigitalGlobe data were provided by NASA's NGA Commercial Archive Data (cad4nasa.gsfc.nasa.gov) under the National Geospatial-Intelligence Agency's NextView license agreement. We thank Kemen G. Austin, Brenna R. Forester, Mariano González-Roglich, and Amanda M. Schwantes for offering valuable feedback. Two anonymous reviewers also provided comments that greatly improved this work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.rse.2017.02.016>.

Fig. 1. Land use and land cover in the Sacramento Valley, within California's Central Valley. (Herbaceous wetlands and agriculture: National Land Cover Database (Homer et al., 2015); flood-irrigated rice: (USDA-NASS, 2014.))

Fig. 2. Landsat surface reflectance data availability (A) and quality (clear fraction identified by the CFmask surface reflectance product) (B) for the Sacramento Valley (WRS-2 path 44/row 33) from February to May 1983–2015.

Fig. 3. Example of inverse distance weighted interpolation, guided by land use survey boundaries (California Department of Water Resources, 2016b) applied to classifications of SLC-off Landsat 7 imagery.

Fig. 4. Receiver operating characteristic (ROC) curves summarizing nine-fold cross validation of water/non-water random forest models used to identify a spring mid-infrared surface reflectance threshold. Dotted lines indicate ROC curves for each fold of the cross validation. The colored line is the average ROC curve; cutoffs for the probability of membership in the water class from 0 to 1 in increments of 0.1 are shown with error bars indicating 95% confidence intervals for the true positive rate and false positive rate at each cutoff.

Fig. 5.

Long-term spring water extent trends from 1983 to 2015 in the Sacramento Valley of California. Significant trends (linear regression, $p < 0.05$) are indicated by a solid line with the equation shown, while non-significant trends are indicated by dashed lines. A significant decrease in water extent in the Sacramento Valley was observed in late March, while a significant increase in water extent was observed in late May.

Fig. 6.

Spring water extent and variability by two-week period in the Sacramento Valley from 1983 to 2015. Boxplots indicate the weighted mean extent and standard deviation of all open water in the valley, as well as water detected within agriculture and herbaceous wetlands for each two-week period in spring. The clear fraction of each Landsat image was used to weight observations.

Fig. 7.

Water extent and frequency for spring months in the Sacramento Valley from 1983 to 2015. Example minimum (top row) and maximum (middle row) water/non-water classifications for each month illustrate the variability of water extent in the study area; the year of each example classification is indicated at the top left of each panel. The frequency of water detection (bottom row) was calculated as the number of times water was identified in each pixel from a stack of all water/non-water classifications for each month from 1983 to 2015, corrected by the total number of cloud-free instances.

Fig. 8. Relativized estimates of spring water frequency within flood-irrigated agriculture (A) and herbaceous wetlands (B) in the Sacramento Valley from 1983 to 2015. Water/non-water classifications were combined for each two-week spring period and the per pixel frequency of water detection was calculated, corrected by the total number of cloud-free instances within each habitat type.

Fig. 9.

Annual water availability compared to spring water extent in flood-irrigated agriculture and herbaceous wetlands in the Sacramento Valley of California from 1983 to 2015. The Water Year Index for the Sacramento River Basin scales annual water availability and designates each year as either 'Critical' (5.4), 'Dry', 'Below Normal', 'Above Normal', or 'Wet' (9.2) (California Department of Water Resources, 2016a). Herbaceous wetland water extent was significantly correlated with the Water Year Index in all spring months; while the relationship was only significant for agricultural water extent in March and April (equations shown for $p < 0.05$).

Table 1

Surface reflectance datasets and reference data sources for confirmed water and non-water locations in the Sacramento Valley of California that were incorporated in water identification threshold optimization. DigitalGlobe data were provided by NASA's NGA Commercial Archive Data (cad4nasa.gsfc.nasa.gov) under the National Geospatial-Intelligence Agency's NextView license agreement. Field data consisted of landscape photographs of the Sacramento Valley collected as part of a separate study (Barbaree et al., 2016).

Surface reflectance data			Reference data			
Sensor	Date	Source	Date	Non-water points	Water points	Extent (km ²)
Landsat 5	2006/5/30	Quickbird	2006/5/25	110	147	349.33
Landsat 5	2008/3/18	Quickbird	2008/3/24	211	153	584.45
Landsat 5	2008/5/4	Quickbird	2008/5/4	205	255	562.73
Landsat 7	2008/5/13	Quickbird	2008/5/9	149	165	1347.66
Landsat 7	2013/1/2	Field data	2013/1/7	42	159	174.64
Landsat 7	2013/4/8	WorldView2	2013/4/10	260	329	1436.78
Landsat 7	2013/5/10	WorldView2	2013/5/18	189	242	1131.67
Landsat 7	2014/1/5	Field data	2014/1/9	199	127	104.95
Landsat 7	2014/3/10	WorldView2	2014/3/15	760	297	2919.3
Landsat 8	2014/1/13	Field data	2014/1/9	181	120	104.95
Landsat 8	2014/3/18	WorldView2, field data	2014/3/15	766	463	3074.06
Landsat 8	2014/4/19	Field data	2014/4/11	516	188	218.63
Total				3588	2645	12009.15

Table 2

Assessment of multiple methods to classify open water from a May 4, 2008 Landsat image of the Sacramento Valley (path/row 44/33) using May 4, 2008 high-resolution Quickbird imagery for reference. DigitalGlobe data were provided by NASA's NGA Commercial Archive Data (cad4nasa.gsfc.nasa.gov) under the National Geospatial-Intelligence Agency's NextView license.

Accuracy	Threshold methods ^{a,c}			Supervised methods ^{b,c}		
	Optimized mid-infrared	Default MNDWI	Optimized MNDWI	Default AWEInsh	Optimized AWEInsh	Maximum likelihood Random forest
Overall	97.33	96.69	95.04	89.88	89.90	99.38
Water producer's	100.00	99.55	90.28	100.00	98.96	98.96
Water user's	95.76	93.67	100	79.32	80.17	98.73
Non-water producer's	93.29	94.25	100	83.45	83.96	83.96
Non-water user's	100.00	99.60	90.28	100.00	99.19	100.00

^aDefault thresholds (value = 0) were applied to the modified normalized difference water index (MNDWI) and automated water extraction index (AWEInsh, non-shadow version). Optimized mid-infrared, MNDWI and AWEInsh thresholds were identified using random forest models trained with 481 water pixels and 492 non-water pixels; receiver operating characteristic curves were used to maximize the true positive rate and minimize the false positive rate.

^bSupervised classifications were trained with randomly selected water (n = 490) and non-water (453 forested, 418 other green vegetation, 460 dry vegetation, and 434 urban/barren) pixels verified from Quickbird imagery. Outputs were reclassified to water/non-water for comparison with other methods.

^cAll methods were evaluated with independent reference pixels (237 water, 247 non-water).

Table 3

Identification of a mid-infrared surface reflectance threshold to map water and non-water in the Sacramento Valley using random forest model cross-validation and receiver operating characteristic (ROC) curve analysis.

Model run ^a	Random forest error estimates			ROC curve results		Threshold accuracy		Overall
	Water	Non-water	Average out-of-bag error	AUC	Probability threshold	Water user's accuracy	Water producer's accuracy	
1	.09	.08	.09	.91	.71	.87	.88	89.13
2	.12	.08	.1	.96	.81	.88	.88	95.71
3	.11	.06	.08	.9	.76	.92	.9	86.4
4	.12	.08	.1	.97	.82	.9	.91	95.43
5	.08	.05	.07	.88	.69	.92	.9	83.97
6	.1	.09	.09	.93	.74	.89	.9	89.16
7	.13	.1	.11	.98	.75	.88	.9	97.53
8	.12	.08	.09	.94	.8	.95	.92	89.95
9	.12	.11	.12	.98	.76	.89	.89	97.53
Average	.11	.08	.1	.94	.76	.9	.9	91.65
CV	12.86	18.83	14.95	3.76	5.66	2.59	1.28	5.17

^aEach random forest model run incorporated water and non-water reference pixels from nine image dates, withholding data from three dates for accuracy assessment. ROC curve analysis identified the probability threshold for membership in the water class that maximized the true positive rate and minimized the false positive rate for each model run.