An integrative modeling approach to mapping wetlands and riparian areas in a heterogeneous Rocky Mountain watershed

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Abstract

Accurate maps of wetlands and riparian areas are critical for targeting conservation and monitoring efforts. However, detailed inventories in mountain regions are largely non-existent, as conventional mapping approaches are hindered by high costs, remoteness, and landscape variability. Contemporary modeling techniques can circumvent many of these issues, but are often difficult to interpret and tend to rely on specialized datasets that prevent their wider application. In this study, we used machine learning, Landsat 8 imagery and geomorphometric indices to map the distribution of wetlands and riparian areas in the Cache la Poudre River watershed, Colorado, USA. We used a presence-background approach to develop and compare predictions from three popular algorithms: boosted regression trees, MaxEnt and random forests. In addition, we developed the models within three elevation-based life zones to account for altitudinal changes in ecohydrology and land use. Our results showed strong predictive performance, with top-performing models achieving area under the curve values as high as 0.98 and correctly classifying up to 95% of test data. Model performance varied by elevation zone, and no algorithm consistently outperformed the others. The boosted regression trees approach was uniquely able to differentiate wetlands from irrigated agriculture and residential areas in lower elevations. Multi-seasonal greenness and wetness indices were highly influential predictors in all models, underscoring the importance of capturing local phenological characteristics and hydrological regimes. Dissection and roughness terrain metrics were key predictors for identifying valley bottom meadows and emergent wetlands in high-elevation forests. We demonstrate how integrating ecological interpretation into the modeling workflow can inform conventional accuracy statistics and help bridge field-based and remote sensing perspectives. We also show how continuous model outputs can facilitate this process by depicting nuances of the wetland-upland continuum. Our approach requires only public data that are widely available, and can be easily adapted to other heterogeneous mountain settings.

Introduction

Wetlands and riparian areas provide numerous ecosystem services, and their increasing loss worldwide demands accurate monitoring for conservation and management. Between 2004 and 2009, losses of wetlands in the United States (U.S.) outpaced wetland gains by 133% (Dahl 2011), while globally, an estimated 50% of wetlands have been eliminated by human activities (LePage 2011). The impacts of these losses are magnified in regions where wetlands occupy only a small portion of the total land area, such as the arid and semi-arid
Regional-scale inventories are important for targeting wetland conservation efforts, yet are often incomplete or outdated due to the time- and cost-intensive nature of field surveys and aerial photograph interpretation. Satellite remote sensing approaches offer a powerful alternative, and an increasing number of studies have shown the efficacy of combining Landsat imagery and ancillary data with regression and machine learning techniques (Baker et al. 2006; Wright and Gallant 2007; Corcoran et al. 2013). These approaches can make use of a range of predictors, fit complex nonlinear relationships and handle missing data and outliers (Lawrence 2004; De’ath 2007; Elith et al. 2008). As a result, they are generally more robust than traditional techniques such as maximum likelihood and classification trees (Ghimire et al. 2012; Lawrence and Moran 2015), and can easily incorporate multivariate imagery and ancillary data important for capturing the range of characteristics associated with wetland systems (Frohn et al. 2012; Corcoran et al. 2013).

Despite these advantages, there remain a number of challenges preventing wider application of such techniques in mountain settings. Wetland and riparian spectral characteristics are determined by a combination of their associated plant communities and their hydrologic regime, both of which exhibit significant variability across space and time (Gallant 2015; Gabrielsen et al. 2016). Considering ecohydrologic dynamics is therefore a key component of effective wetland modeling, and recent studies have demonstrated this in mapping inundation dynamics of coastal wetlands (Jones 2015; Jin et al. 2017) and prairie potholes (Vanderhoof et al. 2016). In mountain regions, a diversity of wetland types and land uses often exist within a single watershed or administrative boundary; landscapes can vary considerably across the elevation gradient, with higher elevations tending to be primarily forest and lower elevations comprising a matrix of urban/sub-urban, rangeland and agriculture. As a result, ecohydrologic processes can produce markedly different spectral values between early spring and late autumn, whereas irrigated agriculture and residential lawns in lower elevations may closely resemble the spectral signatures of nearby riparian areas. This confusion can be exacerbated by the presence of topographic shadow, which is often confused with dark inundated surfaces. In addition, perennial canopy cover from coniferous forests can obscure small wetlands and transitional zones from optical sensors, particularly moderate resolution Landsat data (Corcoran et al. 2015; Gallant 2015). These issues are further compounded by the relative scarcity of wetlands and riparian areas on the landscape, which makes it difficult to distinguish small wetlands nested within larger land cover classes (Wright and Gallant 2007; Millard and Richardson 2015). This combination of temporal and spatial variability – in conjunction with increasing human alteration of landscape processes – presents significant challenges for classification algorithms fitting complex relationships to reflectance and topographic data. As a result, few detailed maps of wetlands or riparian areas exist in any mountain region of North America (Morrison et al. 2015; Salo and Theobald 2016), and are even scarcer in most countries around the world (Tiner 2015).

Many of these issues can be addressed through inclusion of ancillary environmental data such as soil type and bedrock geology, which are consistently among the most influential predictors in wetland distribution models (Baker et al. 2006; Wright and Gallant 2007; Hunter et al. 2012; Corcoran et al. 2013). Topography is also an important control on wetland formation, and hydrogeomorphic data can aid mapping of both wetland and riparian systems (Gumbricht 2015; Salo et al. 2016). This is particularly important in forested regions, as remotely sensed elevation data can describe the vertical structure of terrain obscured by canopy (Corcoran et al. 2015). LiDAR DEMs have been shown to be especially effective for capturing these features (Millard and Richardson 2013; Huang et al. 2014; Millard and Richardson 2015; Corcoran et al. 2015). However, strong reliance on ancillary datasets and their derivatives presents considerable limitations in remote and under-resourced regions where such data are often incomplete or non-existent. Even where data of sufficient coverage and detail are available, the highly specialized skills and software required for data preparation and model development makes regular application a time-intensive and often overwhelming task (Morisette et al. 2013). This not only creates barriers for incorporating field-based ecological knowledge from local experts, but may restrict analysts to the most familiar or readily available classifier. This is problematic, as none of the more modern algorithms are universally better than the others (Leathwick et al. 2006; Aguirre-Gutiérrez et al. 2013; Lawrence and Moran 2015); each performs differently depending on the specific input data, response and the landscape being modeled. As such, relying on a single algorithm ties subsequent predictions to its specific strengths and limitations, which may not necessarily be the best suited to the characteristics of the wetlands in a given region. There is thus a need to develop more user-friendly workflows that facilitate model comparison and interpretation with ecologically meaningful predictors (Michener and Jones 2012; Cord et al. 2013; Pettorelli et al. 2014; He et al. 2015).

A number of recent advances in correlative species distribution modeling and data availability have the potential for addressing the aforementioned challenges. The need
for approaches that make the most of limited data – particularly by the invasive species community – has driven significant development of presence-background modeling. Presence-background approaches estimate the relative likelihood of occurrence of a given response by comparing the environmental characteristics at sites where the response is known to exist (presence) with those throughout the study region (background) (Guillera-Arroita et al. 2015). As such, they are useful for modeling rare classes using limited presence data that is dependable but not perfectly random (Pearce and Boyce 2006). Presence-background approaches also enable the analyst to focus on a single class of interest (as opposed to mapping all classes in a scene), which saves time and resources in model development and can facilitate monitoring efforts (Li and Guo 2010; Mack et al. 2014). These modeling advances are supported by the increasing quality and quantity of publicly available remote sensing data. The Landsat 8 archive is actively being built at an unprecedented temporal and radiometric resolution, and the increased signal-to-noise ratio of its multispectral instrument enables better discrimination among soils and non-photosynthetic vegetation (Roy et al. 2014; Schott et al. 2016). Moreover, the release of 1 arc-second shuttle radar topography mission (SRTM) data offers a globally available digital elevation model (DEM) with a spatial resolution of approximately 30 m at the equator. This, in concert with significant advances in computing power, has created renewed interest in the use of geomorphometry and gradient modeling techniques (Evans et al. 2014; Rigol-Sanchez et al. 2015). Many geomorphometric metrics can be derived directly from a DEM and show promise as important predictors for wetland distribution modeling (Millard and Richardson 2013; Maxwell et al. 2016).

In this study, we explore these emerging techniques for mapping the distribution of wetlands and riparian areas across a heterogeneous Colorado watershed. Our objectives were to: (1) compare the relative performance of three machine learning algorithms developed using a presence-background approach; (2) identify key ecologically meaningful predictors for capturing wetland phenology and geomorphic setting; (3) demonstrate how modeling within elevation-based life zones can reduce landscape heterogeneity and facilitate model interpretation and (4) demonstrate a user-friendly workflow that requires only widely available public data.

Materials and Methods

Study area

The Cache la Poudre River watershed (CLP) is located at the north-central edge of the U.S. state of Colorado and extends across the southern border of the state of Wyoming (Fig. 1). Spanning five counties, the basin’s rapidly growing populations depend on the river for the majority of their municipal and agricultural water. The headwaters of the CLP are located approximately 80 km west of the city of Fort Collins at an elevation of 3280 m (Wohl 2008). From there the river runs for 225 km east down the Front Range, with a flow of approximately $3.5 \times 10^8$ m$^3$ (280 000 acre-feet) annually (Carlson and Lemly 2011), dropping over 2100 m in elevation to its confluence with the South Platte River downstream of the city of Greeley, Colorado.

The Northern Colorado Rocky Mountains are commonly divided into four life zones based on latitude and elevation. Marr (1961) described these as the alpine (above 3475 m), sub-alpine (2835–3475 m); upper montane (2347–2835 m) and lower montane (1829–2347 m). Areas below 1800 m in elevation are typically referred to as the high plains. The CLP is notable in that it crosses all of these regions, each with significantly more homogeneous climate, hydrology, and species composition than the aggregated watershed. Precipitation increases with elevation, and approximately 75% of mean annual precipitation (304–457 mm) occurs between mid-April and late September (Colorado Department of Agriculture 2009). Precipitation in winter months falls as snow (Colorado Department of Agriculture 2009). The alpine zone includes all areas above tree line as well as some sub-alpine fir stands that occur in transitional ecotones (Windell et al. 1986). The sub-alpine zone is generally forested with heavily glaciated terrain, and receives much more variable precipitation than lower elevations. The upper montane and lower montane regions together comprise the largest zone in the watershed, with terrain characterized by steep water-cut canyons and rolling erosional surface uplands (Windell et al. 1986). In contrast, the high plains zone has a semi-arid climate with comparatively level terrain, and contains most of the basin’s human population and agricultural land.

Colorado possesses 15 distinct wetland and riparian systems (Lemly 2010), and plant associations vary with geomorphic and elevation setting, flow regime, slope, and aspect (Naiman and Décamp 1997; Wohl 2001; Carsey et al. 2003). Wetland plant species in mountainous zones are adapted to a very short growing season and long periods of snow cover, whereas lower elevation species are adapted to significantly longer growing seasons with much less precipitation (Windell et al. 1986). Colorado alpine wetlands are largely covered by snow and permafrost throughout the year, and are therefore considered distinct from all other zones (Windell et al. 1986). In sub-alpine regions, fens, wet meadows, and seepage slope wetlands are common, whereas the montane zone
predominantly consists of wet meadows and marshes. In the high plains, riparian areas, conifer swamps, and wet meadows are prevalent (see Figure S1 for example photographs from each zone).

Although wetland types have distinct plant communities, commonly occurring plants in the CLP include shrubs such as *Salix* spp., and *Dasiphora fritica*, and graminoids such as *Carex* spp., and *Juncus* spp., as well as a wide range of forbs. Common tree species include *Populus tremuloides*, *Populus deltoids* and *Populus angustifolia*, as well as occasional upland species including lodgepole pine (*Pinus contorta*), ponderosa pine (*Pinus ponderosa*), Engelmann spruce (*Picea engelmannii*) and sub-alpine fir (*Abies lasiocarpa*) (Colorado Department of Agriculture 2009; Carlson and Lemly 2011). While wetlands and riparian areas are considered ecologically distinct, they possess similar spectral and functional characteristics in the CLP, and we therefore chose to model them as a single class. In this study, we do not aim to predict the distribution of lakes, ponds, or river channels, but rather vegetated areas that are subject to inundation and have overlapping functions; namely, maintenance of water quality, storage of floodwaters, and enhancement of biodiversity (Colorado Natural Heritage Program, 2017).

**Data acquisition and preprocessing**

We acquired a spatial layer of the CLP watershed boundary and its associated National Wetlands Inventory (NWI) polygon data from the U.S. Fish and Wildlife Service (USFWS 2014). The NWI represents the only national-scale database of wetlands in the U.S. and was generated primarily through interpretation of aerial photographs during the 1970s and 1980s. The completeness and accuracy of the NWI varies by region, but it tends toward errors of omission rather than commission, particularly in remote and forested areas. The NWI is often used in conjunction with aerial imagery to generate
datasets for training and testing wetland models (Wright and Gallant 2007; Frohn et al. 2012; Maxwell et al. 2016). The CLP portion of the NWI has seen considerable updates in recent years and is commonly used to guide wetland photo interpretation and field assessments throughout the region (Carlson and Lemly 2011; Sueltenfuss et al. 2013; Lemly et al. 2014).

We acquired four L1T terrain-corrected Landsat 8 images from the U.S. Geological Survey (USGS 2017a,b). All images were captured in 2014 within a single scene (path 34, row 32) and we selected dates related to seasonal variations in each zone’s phenology, hydrology, and land uses (e.g. post-snowmelt in high elevations, pre- and post-harvest for dominant crops in the high plains) (Table 1). Not all images were cloud free across the entire watershed, but each was virtually cloud free within the extent of the life zone(s) it was used to model. The July scene was the exception and contained a few cloudy patches in the montane region; however, we chose not to mask these areas because the coincident pixels were cloud free in the October scene. We used ENVI v5.0 and ArcGIS v10.1 for all Landsat preprocessing. We performed a radiometric calibration to convert the multispectral bands to top of atmosphere reflectance values and the thermal infrared data to brightness temperature values. As our goal was classification and not comparison of a specific value through time, we followed the recommendations of Young et al. (2017) and did not perform further atmospheric correction. This alters the original data values as little as possible in order to avoid the potential introduction of error.

We based our initial list of predictor variables on their known or expected relevance for wetland formation in each elevation zone, which we determined through field observations, consultation with local wetland experts, and the literature (Table 2). For each Landsat image, we derived tasseled cap indices representing brightness, greenness, and wetness across the landscape (Baig et al. 2014). The tasseled cap is a widely used technique that orthogonally transforms multispectral data into new axes similar to the CTI, serves as an estimate of soil moisture (Kauth and Thomas 1976; Crist and Cicone 1984). This provides three interpretable predictors from each image while simultaneously removing much of the covariance inherent among raw Landsat bands. We also included temperature data from the thermal infrared band, which has proven useful for wetland mapping in other mountain settings (Baker et al. 2006). However, we found that thermal band 1 and thermal band 2 were highly correlated in all images, and chose to use only the former in this study.

For topography, we acquired 1 arc-second SRTM DEM data from the U.S. Geological Survey. We used the ArcGIS Spatial Analyst toolbox to create a slope map, and the Geomorphometry and Gradients Metrics toolbox (Evans et al. 2014) to derive a suite of geomorphometric indices. These included dissection (Evans 1972), roughness (Blaszczyński 1997; Riley et al. 1999), compound topographic index (Moore et al. 1993; Gessler et al. 1995), and the integrated moisture index (Iverson et al. 1997). Similar to the topographic position index, dissection is the ratio between the relative relief and the absolute relief of a region. The metric distinguishes ridges from depressions by determining how the elevation of a cell relates to surrounding cell values. Roughness is the unscaled variance of a surface, and can be interpreted as a measure of terrain complexity. Dissection and roughness are both scalable metrics, calculated based on a moving window of a size and shape defined by the analyst. For shape, we used a circular analysis window to mitigate the impact of minor artifacts and striping associated with SRTM data. For size, we chose radii of 2, 4, 8, 16 and 32 cells in an effort to capture the range of ridge to valley bottom distances present in the study site. In the CLP, valley widths in the mountains range from approximately 40 m to 1 km, whereas floodplains in lower elevations can reach widths of approximately 2 km. This resulted in a set of dissection and roughness variables depicting geomorphic features from local- to regional-scales. We derived the compound topographic index (CTI) and integrated moisture index (IMI) to serve as proxies for soil moisture. The CTI is a steady-state wetness index calculated using slope and upstream contributing area to identify areas of topographic convergence. The IMI, which is similar to the CTI, serves as an estimate of soil moisture in topographically heterogeneous landscapes (Evans et al. 2014). The full list of predictors explored in the study is available in Table 2.

**Data preparation**

### Elevation zones

Modeling within ecologically similar spatial subsets increases sampling efficiency, reduces variability, and acts as a useful tool in summarizing landscape characteristics by identifying areas of similar biotic and abiotic

| Elevation zone | Date(s) of images used | Season         |
|---------------|------------------------|----------------|
| High plains   | August 3               | Late summer    |
|               | October 6              | Mid-summer     |
| Montane       | July 2                 | Mid-summer     |
|               | September 20            | Early autumn   |
| Sub-alpine    | September 20            | Early autumn   |

All images were captured in 2014.
conditions (Davis and Dozier 1990; Bara 1994; Stohlgren et al. 2011). To create more homogenous land units, we used the DEM to subset the CLP into life zones based on the elevation breaks defined by Marr (1961) and described in the previous section. We excluded alpine areas from this study due to the lack of NWI coverage in that zone and the persistent snow cover in the available Landsat images. We also chose to combine the upper and lower montane zones to promote larger sample sizes and streamline the modeling workflow.

### Training Data

We used the digital NWI polygons as the basis for generating a highly confident set of presence points across the CLP. First, we selected NWI polygons classified as palustrine (non-tidal, vegetated wetlands lacking flowing water). Prior to sampling, we removed all polygons with area <1 ha, which is a conservative estimate of the minimum mapping unit for identifying wetlands with Landsat data (Wright and Gallant 2007). We then trimmed the margins of the remaining polygons by applying a 30 m buffer to prevent sampling errors due to possible horizontal inaccuracies in the NWI. Following these steps, we randomly generated one point within each refined polygon, resulting in 1973 presence points across the watershed. We visually assessed each of these points through interpretation of 2013 National Agricultural Imagery Program (NAIP) imagery (natural- and false-color infrared, 1 m cell size). This included checking that each point fell within a currently existing wetland or riparian area and was at least 30 m from other points to avoid errors due to spatial autocorrelation (Elith and Leathwick 2009; Millard and Richardson 2015). We also identified and removed any NWI locations that fell within irrigated agricultural plots using the most current polygon data of agricultural land in the region available (CDSS 2010).

This resulted in a final set of 1530 presence points distributed across the three elevation zones: sub-alpine \( n = 398 \); montane \( n = 581 \); high plains \( n = 551 \).

### Modeling

We developed and evaluated all models using the Software for Assisted Habitat Modeling (SAHM; Morisette et al. 2013) developed by the U.S. Geological Survey (Fig. 2). This free software uses the VisTrails interface (Freire et al. 2006) to connect and compare a variety of open source models and code packages. This streamlines the modeling workflow and provides a number of custom tools for preprocessing and evaluation, which can be linked together and run as a series of modules (West et al. 2016). The SAHM is optimized to run presence-absence algorithms using pseudo-absences, and has been used for presence-background modeling of a variety of ecological responses (Evangelista et al. 2016; Jarnevich et al. 2016; Luizza et al. 2016; West et al. 2016).

### Model inputs

We clipped all layers to the extent of each of the three elevation zones using the Projection, Aggregation, Resampling and Clipping (PARC) module within SAHM. We then randomly generated 10,000 background points within the boundary of each zone (Phillips and Dudík 2008; Barbet-Massin et al. 2012), and extracted the value of each predictor at these and the previously generated presence points. Using these values and the Covariate Correlation And Selection module, we created a correlation matrix for all predictors. We then removed redundant predictors to prevent issues related to multicollinearity (Millard and Richardson 2013; Jarnevich et al. 2015); following the recommendations of Dormann et al. (2013),

| Predictor variables | Environmental characteristic | Source data | Reference |
|---------------------|-----------------------------|-------------|-----------|
| Brightness          | Surface albedo; topographic variation | Landsat 8 (OLI) | Baig et al. (2014) |
| Greenness           | Photosynthetic activity      | Landsat 8 (OLI) | Baig et al. (2014) |
| Wetness             | Soil and plant moisture      | Landsat 8 (OLI) | Baig et al. (2014) |
| Brightness temperature | Temperature               | Landsat 8 (TIRS) | U.S. Geological Survey (2016) |
| Slope               | Slope                       | SRTM        | N/A       |
| Dissection (local to regional scales) | Topographic position | SRTM | Evans (1972) |
| Roughness (local to regional scales) | Terrain complexity/variance | SRTM | Blaszczynski (1997); Riley et al. (1999) |
| Compound topographic index | Steady state wetness (estimation of topographic convergence) | SRTM | Moore et al. (1993); Gessler et al. (1995) |
| Integrated moisture index | Soil moisture estimation | SRTM | Iverson et al. (1997) |

OLI, Landsat operational land imager; TIRS, Landsat thermal infrared sensor; SRTM, Shuttle Radar Topography Mission.
we retained only one of each pair of correlated predictors with a Spearman, Pearson, or Kendal correlation coefficient $|r| \geq 0.70$ for use in the final models. We made these selections based on the percent deviance explained from a univariate generalized additive model for each variable and our knowledge of wetland ecology and hydrodynamics in each zone.

**Model development**

We developed a boosted regression trees (BRT; De’ath 2007; Elith et al. 2008), MaxEnt (Phillips et al. 2006) and random forests (RF; Breiman 2001) model for each elevation zone. These represent three of the best-performing and well-established machine learning algorithms for correlative species distribution modeling (Rocchini et al. 2015). The SAHM code is optimized to simultaneously develop multiple models using the same dataset, and we let the program determine model parameter settings to enable direct comparison and support a standardized workflow (Lawrence and Moran 2015). The full list of parameters and their settings are provided in the Appendix (Table S1 in Supporting Information). Each model run produced a continuous surface representing the relative likelihood of wetland or riparian area occurrence across the landscape. We created a binary presence/absence map by applying a statistically determined threshold to the continuous surface, using the value that maximized the sum of sensitivity and specificity (i.e. sensitivity + specificity/2). This is an objective threshold optimization method recommended for use with models developed without true absences (Liu et al. 2013), and can be automatically calculated and applied in SAHM.
Model evaluation

We assessed model performance through a 10-fold cross-validation using the Model Selection Cross Validation module. Cross-validation is repeated data splitting, in which multiple models are developed and tested with results averaged over the repetitions (Hastie et al. 2009). Because it cycles through all of the data, cross validation reduces variability and is less sensitive to erroneous results from a single random selection (Harrell et al. 1996; Jarnevich et al. 2015). Through this process, we calculated a variety of evaluation statistics to assess and compare the predictions for each zone, which allows for a better overall assessment than is possible with a single statistic (Lobo et al. 2008; Jarnevich et al. 2015). The first of these, the area under the receiver operating characteristic curve (AUC), is a threshold-independent metric representing the likelihood of a presence location having a higher predicted value than an absence location (Fielding and Bell 1997; Pearce and Ferrier 2000). AUC has a range of 0–1 (value of 1 represents a perfectly performing model). However, the practical range is 0.5–1, as a value of ≤0.5 would indicate model predictions no better than random. Another evaluation statistic, percent correctly classified (PCC) is the proportion of cross-validated presence and background points correctly classified by the binary map that results from the probability threshold. It is important to note that AUC and PCC weight omission and commission errors equally and their values should therefore be interpreted cautiously when using background points (Lobo et al. 2008; Jiménez-Valverde, 2012; Jarnevich et al. 2015). To supplement these metrics, we also calculated sensitivity, specificity, and the true skill statistic (TSS). Sensitivity is the proportion of positive pixels predicted (1 – omission error rate) and specificity is the proportion of negative pixels predicted (1 – commission error rate) (see Alatorre et al. 2011 for more discussion). Both sensitivity and specificity have a value range of 0–1 (a value of 1 represents perfect performance). The true skill statistic (sensitivity + specificity – 1) is a simple and intuitive metric for assessing the predictive performance of distribution models from presence/absence maps (Allouche et al. 2006). TSS is similar to the traditional kappa statistic, but – like AUC, sensitivity and specificity – is independent of prevalence (the ratio of presence to absence locations). TSS values range from –1 to +1, with +1 indicating perfect agreement and ≤0 indicating a performance no better than random. In addition to these statistics, we used SAHM to create a multivariate environmental similarity surface (MESS) for each run to assess whether model predictions had acceptable levels of extrapolation (Elith et al. 2010; Stohlgren et al. 2011).

Results

Overall assessment

Cross-validation statistics (Table 3) indicated strong predictive performance, with all models achieving test AUC values between 0.92 and 0.98 and correctly classifying 87–95% of test data. Sensitivity (range of 0.71–0.96), specificity (range of 0.87–0.95) and TSS (range of 0.63–0.88) indicated good overall performance, but also revealed variations in predictive power among elevation zones. Visual assessment showed predictions from top-performing models in close agreement with NWI polygons, as well as adjacent wetlands and riparian areas visible in the NAIP imagery (Fig. 3). These results are supported by the MESS analyses, which indicate that the training data sufficiently captured the range of variability in each zone. The few areas where the models did extrapolate beyond the range of sampled values (MESS value <0) were predominantly open water reservoirs and lakes, which is to be expected, as these possess distinctly different characteristics than other image classes. A watershed-scale map comprising the binary predictions from the top-performing model in each elevation zone is provided in Figure 4. Figure S2 includes the continuous and binary raster outputs of the top-performing models in an ArcGIS Map Package. A summary of the final predictors and their influence ranking for each model is provided in the Appendix (Table S2 in Supporting Information). In the following sections, we interpret these rankings within the context of each elevation zone.

Sub-alpine

Landsat September greenness was the most influential predictor across all three sub-alpine models, likely due to the early autumn spectral contrast between sedges and willows and upland conifers. The sub-alpine was the only zone in which terrain metrics were consistently ranked in the top three most influential predictors (Table S2), and we attribute this to the increased topographic complexity and the control this has on wetland formation. For example, the uniquely strong influence of local-scale roughness may be associated with the prevalence of confined and partially confined glaciated channels in the sub-alpine zone. These generally have steeper gradients (the correlation matrix showed local-scale roughness to be highly correlated with slope) and form narrow wetlands and riparian areas. Similarly, we can attribute the influence of regional-scale dissection to the unconfined, glaciated valleys in the zone, which are wider and support extensive wetlands along valley floors.
These geomorphic characteristics also help to explain the contribution of Landsat temperature in this zone. Plant species are stratified based on temperature in sub-alpine wetlands of the Colorado Front Range (Chapin III 1981), and wetlands here experience warmer summer temperatures than adjacent uplands because they lie in valley floors where cool air moves from higher altitudes and drains down valley (Windell et al. 1986). This temperature gradient is evident in the September Landsat thermal band.

All models also showed highly confident predictions of small, isolated wetlands in remote portions of the sub-alpine zone (Fig. 3). Visual comparison with NAIP imagery and their proximity to NWI polygons of similar size and shape suggest these may be previously unmapped emergent and forested wetlands. These are typically under-represented in the NWI (Corcoran et al. 2015) and can form under artesian pressure in areas not shown to be convergent on the surface. The models also showed a number of medium-to-high probability patches located in transitional areas between the alpine and sub-alpine zones (Fig. 3). These likely indicate areas where snowmelt from alpine elevations collects in depressions as well as emerging seepage slope wetlands.

Montane

All algorithms performed well in the montane zone, but only MaxEnt was able to avoid incorrectly predicting into a number of the zone’s small water bodies. The MaxEnt binary map also best captured the boundaries of highly entrenched montane meadows and riparian areas, many only two to three cells wide (Fig. 3). Interestingly, rankings for the top five predictors were nearly identical across all three models (Table S2). The consistent importance of dissection, slope, and roughness can be attributed to the many low-gradient wet meadows that occur in montane valley bottoms. Still, the dominance of September greenness and July wetness emphasizes the role that hydrologic regime has in the montane zone, as wetlands adjacent to running waters tend to be created and maintained by the high water table and seasonal flooding connected to streams (Windell et al. 1986). The snowmelt-driven discharge of Front Range rivers usually peaks in late May–early June (Wohl 2001), and U.S. Geological Survey hydrographs for the CLP Fort Collins stream gauge confirm this for the study year (USGS 2017b). The resulting contrast in moisture between these and adjacent uplands helps to explain the strong influence of early July wetness in all three models. This connectivity to seasonal stream flow also explains the influence of September greenness, since riparian vegetation here tends to remain verdant as upland vegetation begins to senesce.

High plains

Sensitivity was markedly lower in the high plains, indicating higher rates of commission error relative to the higher-elevation zones. This is evident in the false positives observed in a number of irrigated city lawns and agricultural lands. Still, visual assessment revealed that BRT was the only algorithm to avoid considerable confusion in these

### Table 3. Summary of evaluation statistics from the 10-fold cross-validation for each elevation zone.

| Elevation zone | Model | AUC test (AUC train) | Percent correctly classified | Sensitivity | Specificity | TSS |
|----------------|-------|----------------------|-----------------------------|-------------|-------------|-----|
| Sub-alpine     | BRT   | 0.97 (0.99)          | 93                          | 0.89        | 0.93        | 0.82|
|                | MaxEnt| 0.97 (0.97)          | 91                          | 0.94        | 0.90        | 0.85|
|                | RF    | 0.97 (0.97)          | 94                          | 0.86        | 0.95        | 0.81|
|                | BRT   | 0.98 (0.99)          | 94                          | 0.91        | 0.94        | 0.86|
|                | MaxEnt| 0.98 (0.98)          | 92                          | 0.96        | 0.92        | 0.88|
|                | RF    | 0.98 (0.98)          | 95                          | 0.90        | 0.95        | 0.85|
| Montane        | BRT   | 0.93 (0.99)          | 90                          | 0.77        | 0.91        | 0.68|
|                | MaxEnt| 0.93 (0.94)          | 87                          | 0.82        | 0.87        | 0.69|
|                | RF    | 0.92 (0.92)          | 91                          | 0.71        | 0.92        | 0.63|
| High plains    | BRT   | 0.93 (0.99)          | 90                          | 0.77        | 0.91        | 0.68|
|                | MaxEnt| 0.93 (0.94)          | 87                          | 0.82        | 0.87        | 0.69|
|                | RF    | 0.92 (0.92)          | 91                          | 0.71        | 0.92        | 0.63|

Models are boosted regression trees (BRT); MaxEnt and random forests (RF). TSS is true skill statistic.

AUC, area under the receiver operating characteristic curve; BRT, boosted regression trees; RF, random forests

Figure 3. (A) Map of the Cache la Poudre River watershed shown with elevation zones defined by Marr (1961) (see Materials and Methods section) and the presence locations used to develop the models. (B) Examples of predictions from the top-performing model in each zone. The upper row shows high-resolution aerial imagery (displayed in false-color infrared) overlaid with palustrine wetland polygons from the National Wetland Inventory (NWI). The middle row shows the discreet (binary) predictions created by applying a threshold to each continuous surface. The bottom row shows the continuous surfaces which represent the relative likelihood of wetland or riparian area occurrence for each cell. These are displayed using bicubic interpolation to highlight the nuances of the wetland-upland continuum. Comparison among rows shows model predictions aligning closely with NWI polygons as well as capturing adjacent wetland and riparian areas visible in the aerial imagery.

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Integrative Approach to Mapping Mountain Wetlands

A

Sub-alpine | Montane | High Plains

Presence points (NWI)
Alpine zone (excluded)

B

Boosted Regression Trees | MaxEnt | Boosted Regression Trees

NWI Polygons

Binary Predictions

Continuous Predictions

[Legend: Palustrine wetlands (NWI); Predicted wetlands (binary); Relative likelihood: high, low; Predicted wetlands (continuous)]
areas (Fig. 3). Interestingly, BRT was also the only model that showed evidence of overfitting, indicated by the difference in $AUC_{test}$ and $AUC_{train}$ (Table S2). While the practice of avoiding overfitting is common in statistical modeling, the practice can be considered a bias when modeling a naturally complex response (Wolpert 1993; Schaffer 1993). Boosting procedures are inherently prone to overfitting, yet show little impact on performance (Elith et al. 2008), and we posit that the high plains BRT model is in fact capturing the complex and highly variable characteristics of wetlands and riparian areas in the region.

The most influential predictors across all high plains models were October brightness, August wetness, and August greenness (Table S2). While we expected greenness and wetness to make strong contributions, the dominance of October brightness was surprising. Of the three tasseled cap indices, brightness accounts for the most variability in the source image (Baig et al. 2014), and this may explain its influence in the spectrally heterogeneous high plains. Tasseled cap brightness is also associated with bare or partially covered soil (Baig et al. 2014), suggesting that its predictive contribution here stems from the spectral contrast between the exposed ground of post-harvest fields and the moist soils of nearby wetlands. Terrain predictors were considerably less influential in the high plains than in mountainous zones. We attribute this to the region’s relatively flat topography, as well as the highly managed system of irrigation ditches that alter expected flow paths by preventing water from filling some natural depressions while artificially supporting others through canal seepage (Sueltenfuss et al. 2013).

**Discussion**

User-friendly approaches that facilitate the integration of field-based ecological knowledge with remote sensing and
spatial modeling techniques are needed for wetland conservation in mountain regions. Our results demonstrate how such approaches can improve both model development and interpretation in complex landscapes. The consistent and substantial influence of multi-seasonal tasseled cap indices highlights the importance of capturing regional phenological and hydrological characteristics in the Rocky Mountains of Northern Colorado. The dominant role of these predictors in the high plains emphasizes the value of selecting image dates that correspond to planting and harvest cycles of local crops. This is particularly important in regions undergoing anthropogenic alteration of hydrologic regimes, and underscores the need for increased communication among remote sensing analysts and local resource managers.

Geomorphic complexity both reflects and influences processes in river systems, and spatial heterogeneity plays a key role in characterizing these patterns (Wohl 2016). The strong contribution of multi-scale dissection and roughness in the high-elevation zones shows the ability of these metrics to capture the region’s nested geomorphology and its relationship to wetland formation. Conversely, the consistently low influence of CTI and IMI corroborates the findings of other studies (Wright and Gallant 2007; Maxwell et al. 2016). We suspect this is due to the control that seasonality has on soil moisture in the CLP, which is not explicitly accounted for in either metric. Nevertheless, we recommend continued exploration of these and other geomorphometric indices, which should be generated at scales that relate to the range of geomorphic features in the study area. At the same time, we also recommend considering which variables to omit. For example, although stream network derivatives (e.g. ‘distance to streams’) can improve wetland model accuracy (Maxwell et al. 2016), this practice could bias predictions toward wetlands that are more connected to surface hydrology (or simply the flow lines in the dataset being used). This may diminish the response of groundwater-fed riparian areas (Cadol and Wine 2017) and isolated wetlands that would have otherwise been identified by the model. Therefore, we recommend developing initial models using only carefully selected spectral and terrain variables, assessing the results, and then adding ancillary variables as necessary.

Our focus was on creating baseline maps of wetlands vs. uplands. However, our modeling approach may also hold potential for integration with existing wetland typologies. Multi-seasonal ecohydrologic and geomorphometric variables may provide machine learning algorithms with enough information about hydrodynamics and topographic setting to accurately predict hydrogeomorphic classes. This would enable landscape-scale mapping and monitoring of wetland function, and is a key area for future research. Comparison modeling will remain an important tool for such studies, as different algorithms will be better suited for different typologies and landscapes.

It is important to note that our models represent correlation between known locations and a given set of environmental variables; therefore they should not be interpreted as definitive or causal explanations of wetland distribution, but rather possible or probable conclusions that can be improved upon with the incorporation of additional field data and modeling (Jarnevich et al. 2015). While this makes it impossible to assess their accuracy and uncertainty using conventional metrics used in remote sensing literature (see Olofsson et al. 2014 and Stehman et al. 2004), it is arguably a more appropriate approach for mapping an image class that is so highly dynamic and lacks a unifying land surface feature (Gallant 2015). Wetlands and riparian areas are ‘moving targets’ from a remote sensing perspective, comprising more of a moisture regime than a cover type (Gallant 2015). We found the continuous model outputs to provide a valuable depiction of the natural wetland gradient in our study area, highlighting nuances of the land-water continuum not shown in the discreet maps. These continuous maps also mitigate limitations of Landsat’s moderate spatial resolution; rather than discarding information embedded in mixed pixels, the user is provided with a gradient of confidence with which to interpret the ecotones that form at the wetland-upland interface (Adam et al. 2010). This may help capture forested and emergent wetlands that are difficult to identify from aerial imagery. Still, end-users can also benefit from conservative estimates provided by binary maps, as these can be used to calculate descriptive statistics (e.g. count, area) and serve as inputs for studies on wetland patch dynamics and fragmentation. Binary maps can be generated from the continuous surface using a threshold that fits the needs of the user (Jarnevich et al. 2015). For example if the goal is a conservative map for targeting field assessments, a higher threshold that maximizes sensitivity may be desirable. However, a lower threshold may be more appropriate if the goal is to identify emergent or ephemeral wetlands, provided the greater likelihood of false-positives is acceptable. Given this flexibility, we recommend the use of both continuous and binary model outputs, as each provides valuable information and can be automatically generated within SAHM.

Conclusions

We explored the use of publicly available data and presence-background modeling for mapping the distribution of wetlands and riparian areas in a heterogeneous Rocky Mountain watershed. Our results underscore the importance of comparison modeling, as none of the three algorithms that we compared consistently outperformed the others. However, the unique ability of boosted regression trees to avoid major
confusion with irrigated agriculture and residential lawns shows promise for remote sensing of wetlands in other managed landscapes with confounding cover classes. The strong influence of multi-seasonal tasseled cap indices – particularly in regions with significant human alteration – demonstrates the importance of selecting image dates that relate not only to wetland phenology and hydrologic regime, but also to local land use and crop cycles. These techniques should be used in conjunction with scalable dissection and roughness metrics, which we found to be key predictors of wetland distribution in complex geomorphic settings. We also demonstrated the use of elevation-based life zones for developing wetland models in mountain regions. This not only reduces variability, but also facilitates interpretation by situating increasingly complex classification techniques within well-understood ecological frameworks. This provides context and nuance to conventional accuracy statistics, and serves as a bridge between modeling and field-based perspectives.

Acknowledgments

This study was conducted at the Natural Resource Ecology Laboratory and the Geospatial Centroid at Colorado State University, as well as the U.S. Geological Survey Fort Collins Science Center. The material is based upon work supported by the National Aeronautics and Space Administration under award No. NNX14AB60A. Thanks to those who contributed to early stages of this project: Amy Birtwistle, Kelli Groy, Brenda Kessenich, Aaron Sider, Anthony Vorster and Amber Weimer. Additional thanks to Jeremy Sueltenfuss and Gabrielle Smith from the Colorado Natural Heritage Program, David Merritt from the U.S. Forest Service, Catherine Jarnevich and Jeffrey Morisette from the U.S. Geological Survey and Stephanie Kampf, Melinda Laituri, Sophia Linn, and Ellen Wohl from Colorado State University. We also thank the two anonymous reviewers whose suggestions considerably improved the quality of the final manuscript.

Conflict of Interest

None declared.

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**Supporting Information**

Additional supporting information may be found online in the supporting information tab for this article.

**Table S1.** Parameter settings for each model developed using the Software for Assisted Habitat Modeling (SAHM).

**Table S2.** Influence rankings of predictors used to develop each of the models.

**Figure S1.** Examples of different types of wetlands that occur in the Cache la Poudre River watershed and northern Colorado (not comprehensive).

**Figure S2.** ArcGIS Map Package (.mpk) comprising the symbolized raster outputs of the top-performing models for each elevation zone.