A Comparison of Remotely Sensed Environmental Predictors for Avian Distributions: Supplemental Material

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Online Resource 1.

Description of image processing workflow

First, we developed a time series of seasonal, 30 m satellite image composites over the state of Oregon using data acquired by the Landsat program. We obtained imagery from the United States Geologic Survey's (USGS) Landsat Collection 1 Tier 1 surface reflectance dataset. We aggregated all Landsat Thematic Mapper (TM), Enhanced Thematic Mapper plus (ETM+), and Operational Land Imager (OLI) scenes which intersected our study area and had less than 85% cloud cover. We harmonized the spectral values of the imagery acquired by the OLI sensor with the TM/ETM+ sensors using the reduced major axis regression coefficients from Roy et al. (2016). Clouds and cloud shadows were removed from the imagery with the FMask algorithm (Zhu and Woodcock 2012). We then divided the time-series of images into three seasons: Spring (Julian days 105 - 196), Summer (Julian days 166 - 259), Fall (Julian days 227 - 319) (Hooper and Kennedy 2018). Lastly, we processed each seasonal subset of images into a time-series of annual composited imagery using the medoid method (Flood 2013).

Next, we processed each of the seasonal time-series of medoid composites individually with the LandTrendr (Kennedy et al. 2010) algorithm to construct a radiometrically consistent time series of gap-free mosaics. First, for a given time series of medoid composites, we computed a time-series of Normalized Burn Ratio (NBR) values (Key and Benson 1999). Next, we input the time-series of NBR images into the LandTrendr algorithm to perform temporal segmentation (Kennedy et al. 2010, 2018). The LandTrendr algorithm fits a piecewise-linear model to the time-series of NBR values at each pixel location (hereafter referred to as a pixel-series). The fitting process consists of first creating a maximally complex model and then generating a series of successively simpler models by iteratively removing segments with the lowest contribution to the model's mean squared error. The final model for a given pixel-series is selected using the p-value of the F-statistic (see Kennedy et al. 2010 for details).

Following the initial segmentation of the time-series, fitted values for other spectral bands or indices can be obtained by imposing the breakpoints (i.e., the start and/or end point of a linear segment) identified by the LandTrendr algorithm onto each of the spectral bands (see Kennedy et al. 2015 for details). The fitting process removes ephemeral noise that can be introduced by variations in image acquisition timing, variations in atmospheric conditions, and errors in the cloud masking processes. We parameterized LandTrendr to allow for more flexible model fitting. This enabled the algorithm to effectively respond to both abrupt disturbances (e.g., land cover change, clearcuts, fire) and gradual change processes (e.g., insect outbreaks, forest degradation). Additionally, the LandTrendr models provided a sensible way to interpolate any image gaps in the time-series (though, in the years of the analysis, image gaps were small and sparse).

In addition to the raw bands from each of the three seasonal time-series of LandTrendr fitted imagery, we calculated the Tasseled Cap transformation, several derived indices (Table 2), and Gray Level Co-occurrence Matrices (GLCM) texture metrics (Table 3). We computed the GLCM texture metrics using two spectral bands, B4 (near-infrared) and B7 (shortwave-infrared) (Table 3). For each of the two spectral bands, we calculated the texture metrics using four angular offsets [(-1, -1), (0, -1), (1, -1) and (-1, 0)] which were then averaged together (see Haralick et al. 1973 for details).

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