EXPLANATION FOR WETLAND LANDSCAPE DATASET

Explanation Version: September 2021

This explanation describes wetland landscape data compiled by the Utah Geological Survey (UGS) with funding from the Environmental Protection Agency's Wetland Program Development Grants and made available through a database download and via an online application. More detailed information about the fields included in the dataset are in the associated spreadsheets. Fields are organized into categories in the spreadsheet, which are referenced in the text below.

DATA OVERVIEW

The landscape dataset summarizes information on where and what kinds of wetlands are in Utah, who owns those wetlands, how ownership patterns differ from overall land ownership patterns, and locations with potentially restorable wetlands. These data also summarize trends in groundwater and surface water resources across the state. Data are summarized at five spatial scales based on hydrologic unit boundaries and ecoregions. Hydrologic units represent the area of the landscape that drains to a particular location in a stream network (or to multiple outlet points in areas with diffuse flow). Hydrologic units are organized in a hierarchical system with the largest unit, the hydrologic unit code 2 (HUC2), divided into smaller and smaller units down to the HUC12 level. Ecoregions are areas where ecosystems are generally similar based on patterns related to geology, landforms, soils, vegetation, climate, land use, wildlife and hydrology. We summarized data for HUC12s, HUC8s, and level III Omernik (1995) ecoregions as well as HUC12s and HUC8s split by ecoregion. The five scales included in the dataset, in order from smallest to largest, are HUC12 split by ecoregion, HUC12, HUC8 split by ecoregion, HUC8, and ecoregion. Individual polygons within each scale are referred to as "analytical units" in subsequent text.

The project area was set as the full extent of all HUC8s that overlap Utah, which includes parts of neighboring states. Data were first summarized in the statistical program R at the smallest spatial scales and then combined to create datasets at the remaining four scales. Fields at each scale are identical except for groundwater and surface water trend data, which were only calculated at one or two scales each. All data obtained for this project were clipped to the project boundary and reprojected as NAD83 UTM 12N before further processing.

DETAILED DESCRIPTION

Watershed, Ecoregion, Area, and Percent Utah

Hydrologic unit data were obtained from the Watershed Boundary Dataset (U.S. Geological Survey National Geospatial Program, 2020) and ecoregional data were obtained from Omernik (1995). Fields in the ***location*** category provide information on the watershed identifier and the ecoregion name. Total area of each analytical unit was calculated in ArcGIS and the percent of the analytical unit located within Utah was calculated using state boundary data from the Utah Geospatial Reference Center (UGRC).

Wetland and Riparian Data

Wetland and riparian data and metadata were obtained from the National Wetlands Inventory (NWI). Most of the data were obtained directly from the U.S. Fish and Wildlife Service via a file sharing site (J. Ingebristen, U.S. Fish and Wildlife Service, written communication, January 2021), though some of the shared data were missing metadata or riparian data. For missing data, we used data from the NWI data download portal (U.S. Fish and Wildlife Service, 2020). Wetland spatial data are available across the entire project area, though much of the data are out-of-date and were created using older mapping standards. Variables in the ***wetland metadata*** category indicate the percent of area within the analytical unit that has outdated mapping (mapping using pre-2000 imagery or imagery with >1-m resolution), high-resolution mapping with imagery between 2000 and 2009, and high-resolution mapping with imagery between 2010 and 2019.

We classified wetland spatial data as one of six aquatic resource types (table 1) and then summarized the data in each analytical unit in three ways, including 1) a ***count*** of unique features, 2) the total ***area*** of the features, and 3) the ***density*** of features. Types were primarily derived from the NWI wetland types, except that we split features classified as "Lake" into two types depending on if the features held water all year (NWI classes unconsolidated bottom, rocky bottom or aquatic bed) or were drier shores, salt flats, or unvegetated wetlands (NWI classes unconsolidated shore or rocky shore).

Table 1. UGS types used to summarize wetland spatial and ownership data, including a general description and crosswalk to NWI types.

Aquatic Resource Type	**Ownership Ratio Class**	**Description**	**NWI Type**
Riverine	Riverine	Rivers, channels, and bars	Riverine
Lake	Waterbody	Lakes	Lake (classes unconsolidated bottom, rocky bottom, and aquatic bed)
Pond	Waterbody	Ponds	Pond
Shore	Waterbody	Shores, salt flats, and unvegetated wetlands	Lake (classes unconsolidated shore or rocky shore)
Woody	Vegetated	Woody wetlands	Freshwater Forested/Shrub Wetland
Emergent	Vegetated	Emergent wetlands	Freshwater Emergent Wetland and Other[1]

[1]Palustrine farmed features were mapped as wetland type "Other."

National Wetlands Inventory data only include riparian mapping data for a small part of the state. We summarized riparian metadata to indicate the percent of each analytical unit having riparian mapping data. Riparian data are classified into one of two types—emergent or woody—and then summarized by calculating the total mapped area of each type.

Ownership

We used two sources of land ownership data: 1) National Surface Management Agency (SMA) Area Polygons (Bureau of Land Management, 2020) and 2) Land Ownership for Utah from the UGRC (SITLA, BLM, and Partners, 2021). We found both datasets to have 99.7% agreement in determining private, state, federal or tribal ownership in areas where they overlapped and primarily used the SMA data as it was available throughout the project area. We addressed all coverage gaps, polygon overlaps, and missing ownership attribution by merging features with missing data less than one hectare in size with the nearest adjacent feature; running topology to fix overlaps; assigning features with missing ownership information to the ownership class assigned by SITLA, BLM, and Partners (2021) when possible; and assigning features outside Utah with missing ownership information to adjacent ownership classes.

Once the data were processed, we calculated three types of metrics. First, we calculated metrics in the ***unit ownership*** category that summarized the percent of the analytical unit having private, state, federal, and tribal ownership. Next, we calculated ***wetland ownership*** metrics to show the ownership patterns for different types of aquatic resources. We classified aquatic resources into three classes (table 1), including riverine, waterbody (pond, lake, and shore), and vegetated (woody and emergent), and determined the percent of area in each class that is under private, state, federal, or tribal ownership. Last, we calculated metrics in the ***ownership ratio*** category to compare the ratio between the percent privately owned wetland of a particular class (riverine, waterbody, or vegetated) divided by the percent of the total analytical unit privately owned. Values greater than one indicate disproportionate private ownership of a particular wetland class and values less than one indicate disproportionate tribal, federal, or state ownership.

Potentially Restorable Wetlands on Agricultural Land

The Potentially Restorable Wetlands on Agricultural Land is a dataset created by the Environmental Protection Agency (2021) that depicts the location of agricultural areas that naturally accumulate water and may have poorly drained soils. The dataset was created using a combination of modeled land cover data from the National Land Cover Database, soils data from the Natural Resources Conservation Service, and a wetness index (Bryce and Horvath, 2019). The dataset classifies land as unsuitable, low, moderate, or high wetland restoration potential. We used the data to calculate the percent of each analytical unit that was classified as having a moderate or high likelihood of being a restorable wetland.

Groundwater Levels

Groundwater well data for wells that overlapped the project area were downloaded from the USGS using the dataRetrieval package in R (DeCicco and others, 2018). We processed the data to obtain one water level value per year per well, preferentially using values recorded in the spring months (typically March) whenever possible. If no level was recorded during the spring, we used a water level from later in the year if available. To better examine long-term trends in groundwater levels, we pared down the available data to wells with records that started no later than 1965 and having at least 50 years of data through 2020 and no more than three consecutive years of missing data. Water level data from before 1960 were also excluded to create a consistent period of analysis. Based on these exclusions, we analyzed water level data from 241 wells, with 32 of the 67 HUC8s in the project area containing at least one of these wells. These 32 HUC8s contained a median of 4 wells and mean of 7.5 wells. Well hole depth was not considered in the selection process, and water levels in wells ranged from -66.5 to 305.37 feet below the surface.

We conducted a Mann-Kendall trend analysis to test for significant increasing or decreasing trends in water levels. We checked for autocorrelation for each well and applied a Mann-Kendall Trend test without modifications when we found no autocorrelation, a modified Mann-Kendall Test using the Yue and Wang (2004) variance correction approach with the lag-1 correlation coefficient when there was correlation at lag 1, or a modified Mann-Kendall test using the Yue and Wang (2004) variance correction approach when we found correlation at multiple lags, using the mkttest, mmky1lag, and mmky functions in the modifiedmk R package, respectively (Patakamuri and O'Brien, 2020). These functions also calculate a Sen's slope value, a nonparametric estimate of the slope of a trend (Sen, 1968). We used an alpha level of 0.01 for all statistical tests due to the large number of comparisons.

We summarized the resulting data by HUC8 in ***groundwater level*** metrics to show the total number of wells in the HUC8 and the percent of wells with significant rising and falling trends. We also calculated the mean Sen's slope for wells that were significantly falling or rising in each HUC8. We did not calculate summarized well data at other spatial scales due to a high number of analytical units that would have had no data at finer spatial scales.

Surface Water Extent

We used the JRC Monthly Water History data available in Google Earth Engine to examine trends in surface water extent from 1990 to 2019 for HUC12s and HUC8s in the project area (Pekel and others, 2016). The JRC Monthly Water History data depict the location of open surface water (i.e., water not obscured by vegetation) between the years 1984 and 2020 across the entire Earth. The data are derived by classifying pixels from images from Landsat 5, 7, and 8 satellites.

For each area of interest, we calculated the mean area of surface water extent from May to September for each year. The May to September window was chosen because those five months had the most data available and coincided with the growing season across much of Utah. If a month had more than 20% missing data (because of clouds, etc.) we excluded it from the average. We used a NAD83 Conus Albers projection to conserve area in our calculations. All analysis was done in Google Earth Engine and R (Gorelick and others, 2017; R Core Development Team, 2020). To see whether the surface water trends over time were significant, we ran a Mann Kendall analysis with the modifiedmk package in R on each area, accounting for temporal autocorrelation when appropriate with the mmky1lag or mmky test (Patakamuri and O'Brien, 2020). We did not run a Mann Kendall test when sites had less than 10 years with water present within the area of interest. We used an alpha level of 0.05 for tests in the HUC8s and an alpha level of 0.01 for tests in the HUC12s, due to the large number of analytical units at the latter watershed scale.

We selected a subset of HUC12 watersheds with significant trends to evaluate trend accuracy, determine major drivers of trends, and evaluate the relationship between trend accuracy and the amount of surface water present. We randomly selected 20 HUC12s with significant trends in each of three water cover categories: 1) low (<0.1% of analytical unit covered with water during at least one month of study period), 2) medium (0.1 to 1% water), and 3) high (>1% water). We then examined available aerial imagery from Google Earth and the UGRC's imagery and base map server. Google Earth displays imagery sourced from a variety of satellite companies that are combined into a mosaic of images taken over many days, months, and years. Data from the UGRC includes black-and-white imagery from the 1990s and NAIP from 2006, 2009, 2011, 2014, 2016, and 2018. Each HUC12 was assigned a confidence score ranging from -3 to 3 to describe confidence in the assigned trend. Negative values indicate trends that appear inaccurate based on visual examination and positive values indicate trends that appear accurate, with values closer to -3 or 3 indicating stronger confidence in assessment. Values of zero indicated no confidence in evaluating the accuracy of the trend.

Of the 60 HUC12s examined, only 4 had trends that appeared to be incorrect, though 14 others were assigned a confidence value of zero. We had a similar level of confidence in increasing and decreasing trends. Twenty-eight HUC12s had trends of increasing surface water that were deemed likely accurate (confidence value of 1 or higher). These included 16 sites with visible evidence of new ponds or impoundments, 9 sites where existing reservoirs or lakes appear fuller over time, and 3 other sites. Fourteen HUC12s had declining surface water trends and were deemed likely accurate; these primarily contained lakes, ponds, or less frequently, rivers that appeared in imagery to decline over time. Inaccurate trends were equally common in the low and high surface water category, although the low surface water category had the most sites with confidence values of 0 (table 2). Based on these results, we decided not to report trends for sites within the low surface water category, though we still include the resulting Mann-Kendall analysis statistics. Although surface water extent data generally seemed accurate during our review, we did observe that some locations with shadows were sometimes mapped as water and noted that it was difficult to evaluate salt flats and rivers.

Table 2. Accuracy assessment results depicting the number of HUC12s with accurate-appearing trends based on evaluation with aerial imagery.

Surface Water Category	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**% Likely Accurate**
Low	2	0	0	7	2	0	9	55.0%
Moderate	0	0	0	4	7	4	5	80.0%
High	0	0	2	3	3	7	5	75.0%

We report five variables in the ***surface water*** category, as well as a plot of annual surface water extent between 1990 and 2019. The variables we report include trend, Sen's slope, Kendall's tau, lag used in analysis, and p-value. Trend includes Decreasing, Increasing, No Trend, and No Data. Trends classified as No Data include analytical units with too few years of data to run analysis and analytical units with less than 0.1% maximum surface water.

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