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GDE Pulse: Taking the Pulse of Groundwater Dependent Ecosystems with Satellite Data

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Abstract

Remotely sensed data from satellites have been used to monitor the health of vegetation across the globe since the 1970s. With current advances in computing, data processing capabilities, and easy access to satellite data,we are now able to develop methods to efficiently monitor natural systems in near real-time. The GDE Pulse web app developed by The Nature Conservancy provides users easy access to satellite data to view long term temporal trends of vegetation metrics. These vegetation metrics serve as an indicator of vegetation health for Groundwater Dependent Ecosystems (GDEs). In addition, the GDE Pulse web app provides long-term temporal trends of groundwater depth and regional precipitation data. This provides users with a platform to infer relationships between groundwater levels, precipitation, and GDE vegetation metrics to monitor and sustainably manage groundwater and GDEs.

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Introduction

Groundwater dependent ecosystem (GDE) are plant and animal communities that solely or partially depend on the availability of groundwater to maintain their structure and function (Murray et al. 2003; Eamus and Froend 2006). GDEs are specifically defined under California's Sustainable Groundwater Management Act (SGMA) as “ecological communities or species that depend on groundwater emerging from aquifers or on groundwater occurring near the ground surface.” (Cal. Code Regs. tit. 23, §351(m), 2019). GDEs provide valuable functions that benefit people, such as purifying water, providing recreational opportunities, climate regulation, pollinators for nearby agricultural fields, and habitat for endangered species (Griebler and Avramov 2015).

The health of GDEs are affected by a variety of factors, including climate, pests, land management, water quality, and their ability to access groundwater (Brown et al. 2011; Groeneveld 2008; Patten, Rouse, and Stromberg 2008; Cooper et al. 2006; Elmore et al. 2006; Huntington et al. 2016). Klove et al. (2011) in a review highlighted the significance of groundwater for different GDEs and highlighted the status and future risks of GDEs under altered climate and land use practices (Kløve et al. 2011). Removal or a change in the timing, quantity, quality, or distribution of groundwater can negatively influence these ecosystems and associated fauna assemblages, thus emphasizing the importance of monitoring groundwater levels and GDEs (Murray et al. 2003). The health of a GDE can be measured through a variety of metrics, including growth, species diversity, reproduction, interactions between species, and survivorship (the percent of plants that are alive from one year to the next) (Rohde et al., in review). Ground based metrics are ideal for monitoring GDE health, but this information is expensive to collect and not available at a statewide scale.

Remotely sensed satellite data can provide a cost effective alternative to routinely monitor GDEs statewide. Remote sensing methods take advantage of different patterns of reflectance related to the level of surface moisture and/or photosynthetic chlorophyll present in vegetation. In the absence of field-based biophysical monitoring data, remotely sensed indices associated with vegetation moisture and chlorophyll can provide an indirect metric of growth and water stress. Both of these variables provide a preliminary proxy to monitor GDE health. Many studies have demonstrated the utility of satellite remote sensing to monitoring metrics of vegetation health like vigor, growth, and mortality using different spectral indices (Vogelmann et al. 2012; Huang et al. 2010; Asner et al. 2016; Healey et al. 2018). Free and easily available satellite data from Landsat sensors since 1984 presents a tremendous opportunity to evaluate the long-term trends of change in greenness and moisture content of GDEs over time. Researchers have also found that remotely sensed vegetation metrics, precipitation, and groundwater levels near GDEs are correlated and help to better understand the impact of groundwater extraction on GDE health (Huntington et al. 2016; Groeneveld 2008).

The influence of groundwater levels on GDE health is highly site-specific, and understanding this relationship requires an understanding of the local geology, aquifer parameters, land use history, and surface water deliveries. Many groundwater managers have this information for their local area, so the GDE Pulse tool can be used to augment local knowledge to enable ecosystems to be considered under sustainable groundwater management. The GDE Pulse tool provides groundwater managers with critical information to help them better understand the interplay and correlations between GDE vegetation metrics, local precipitation, and groundwater levels.

Methods and Data Sources

Indicators of Groundwater Dependent Ecosystems

The indicators of GDEs (iGDEs) data used in the GDE Pulse web app are derived from the vegetation data included in the Natural Communities Commonly Associated with Groundwater Dataset (NCCAG or NC Dataset) (Klausmeyer et al. 2018). The data were downloaded from the California Natural Resources Agency Open Data platform in January 2019. To summarize the satellite data for each iGDE polygon, the iGDE polygons were converted to a raster grid that has the same resolution (~30 meter) as the Landsat satellite data using a rule that a grid cell was only included if >50% of the cell was included in a polygon. This minimizes the edge effects since many iGDEs border irrigated agriculture fields which have very different spectral signatures. Some iGDE polygons were too small to include >50% of a Landsat grid cell. These are included in the GDE Pulse mapping application, but have no Landsat data summarized for them.

Remote Sensing and Vegetation Metrics

The Landsat mission launched by NASA in 1972 is the longest satellite monitoring program and has continuously acquired space-based moderate resolution (~30 m) images of the Earth's surface every 16 days. The Landsat satellites include four primary sensors that have evolved over thirty years: MSS (multi-spectral), TM (Thematic Mapper), ETM+ (Enhanced Thematic Mapper) and the Operational Land Imager (OLI). Each Landsat scene is comprised of multiple spectral bands. The spectral bands are designed to record visible, near-infrared, middle-infrared and thermal wavelengths reflected from the Earth's surface.

Landsat data products are continually evolving and being refined to improve quality and ease of access. Currently pre-processed cloud-free images comprised of 6-8 bands from TM, ETM and OLI are available through an application program interface (API) called Google Earth Engine (GEE) (Gorelick et al. 2017). These datasets are available across the entire state and as new images are collected they are made available to users on GEE in near-real time through Google's computing infrastructure. For this study we ingested all surface reflectance corrected multispectral Landsat imagery (Landsat 5 TM, Landsat 7 ETM+ SLC on, and Landsat 8 OLI) available within GEE from 1984 to 2018 across the entire state of California. Imagery were processed further to mask clouds and cloud shadows using the CFmask algorithm (Zhu, Wang, and Woodcock 2015). We calculated the medoid (a multi-dimensional feature space median) for each year to reduce the spectral observations from the Landsat record to a set of 34 images - one for each year. We chose a timeframe of July 9 to September 7 for each year because GDE species are more likely using groundwater during the dry months than other times of the year (Huntington et al. 2016).

Using the annual dry-month medoids, we calculated the Normalized Derived Vegetation Index (NDVI) to estimate vegetation greenness and Normalized Derived Moisture Index (NDMI) to estimate vegetation moisture (Table 1). These vegetation metrics (VMs) were selected based on their documented relationship to the presence of photosynthetic chlorophyll or moisture (see sources in Table 1) and ability to provide a proxy for vegetation growth and water stress, which are helpful variables for inferring ecosystem health. Living vegetation absorbs radiation in portions of the visible spectrum and reflects in the near-infrared (NIR), whereas radiation in the red as well as shortwave-infrared (SWIR) is absorbed by water present in the vegetation. Therefore, NIR and red wavelengths are sensitive to variations in photosynthetic chlorophyll, and SWIR wavelengths are sensitive to variations in moisture. Numerous spectral vegetation indices have been used to study vegetation health, drought impacts on vegetation, and deforestation. NDVI is the most widely used VM in the literature and is a reliable measure of the photosynthetic chlorophyll content in leaves and vegetation cover (Figure 1) (Rouse et al. 1974; Jiang et al. 2006). NDVI has been used in several studies to identify terrestrial ecosystems and wetlands that depend on groundwater based on the principle that ecosystems that are able to maintain consistent greenness during a prolonged dry period, are defined as potentially groundwater-dependent (Gou, Gonzales, and Miller 2015; Barron et al. 2014; Doody et al. 2017). NDMI is based on the NIR and SWIR bands and is also widely used in the literature as a metric of vegetation moisture stress (Wilson and Sader 2002; Jin and Sader 2005)

Spectral Index	Equation	Source
NDVI	NDVI = (NIR – red)/(NIR + red)	(Rouse et al. 1974)
NDMI	NDMI = (NIR – SWIR)/(NIR + SWIR1)	(Wilson and Sader 2002)

Table 1: Vegetation Metrics in GDE Pulse

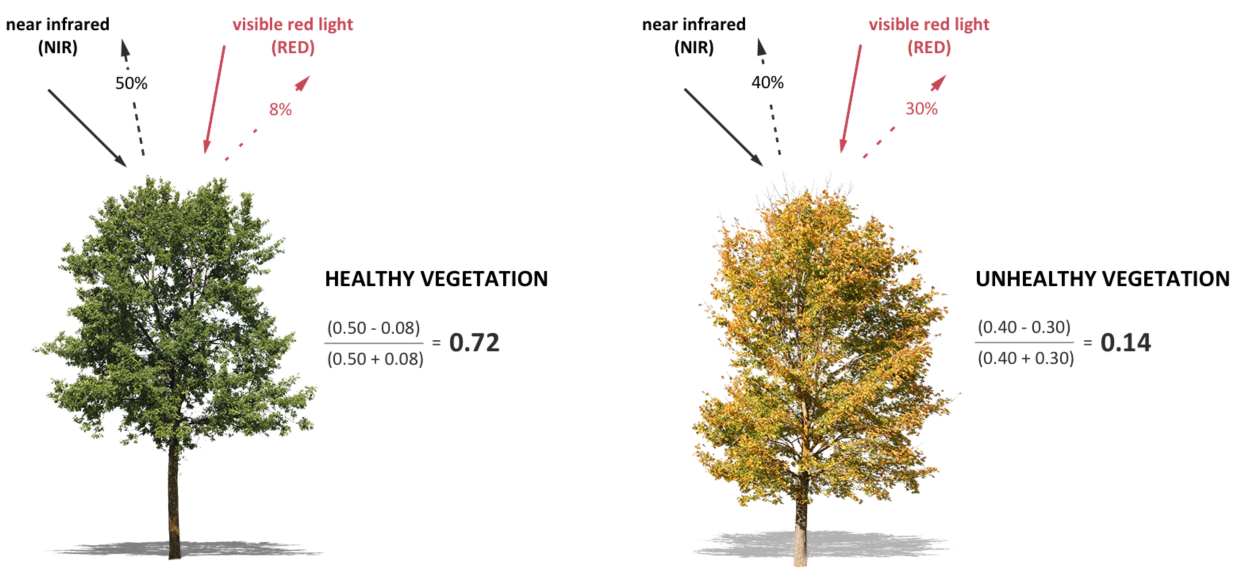

Figure 1. This image shows how much light is absorbed or reflected by healthy vegetation compared to unhealthy vegetation. The reflected values are used to generate the NDVI index, with healthy vegetation typically having a higher value than unhealthy vegetation. (Illustration inspired by Robert Simmon, Source NASA).

After calculating NDVI and NDMI for the annual dry-month medoid Landsat image, we masked the data to the iGDE polygon mask described above. We then summarized the average NDVI and NDMI for all the Landsat pixels that fall within each iGDE polygon for each year. We calculated the linear trend in NDVI and NDMI for three different periods (1985-2018, 2009-2018, and 2014-2010) for each landsat pixel within the iGDE polygon mask. These averages and trend layers are available on the GDE Pulse web-map and allow the user to quickly see positive or negative trends in the two vegetation metrics at the native resolution of the landsat data.

Precipitation

Vegetation metrics like NDVI and NDMI could also be affected by local precipitation, so we summarize the annual precipitation for each iGDE polygon. We used the monthly Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation data at 2.5 arc-second resolution (~ 4 km) available in GEE (Daly, Smith, and Olson 2015; Daly et al. 2008). We summarized the data using the water year (October 1-September 30).

Groundwater Depth Data

The groundwater depth data is derived from the California Department of Water Resources (DWR) Periodic Groundwater Level Measurement dataset (https://data.cnra.ca.gov/dataset/periodic-groundwater-level-measurements). This dataset includes depth to groundwater measurements collected by DWR and other cooperating agencies including the U.S. Geological Survey, as well as information about the groundwater well (type, location, depth, perforated intervals). We classified the wells to estimate if the measurements reflect conditions in a shallow surficial aquifer or a deep confined aquifer (Figure 2). The measurements from shallow unconfined aquifers are most relevant to GDE health because the roots typically do not penetrate confining layers or extend below ~70 feet below the ground surface (Stromberg 2013; Fan et al. 2017). We classified wells as "Shallow Aquifer" if the total depth is 100 feet or less, or the top of the shallowest perforation is 100 feet deep or less. "Deep Aquifer" wells are deeper than 500 feet or the top of the shallowest perforation is deeper than 200 feet. All other wells were classified as "Uncertain Aquifer".

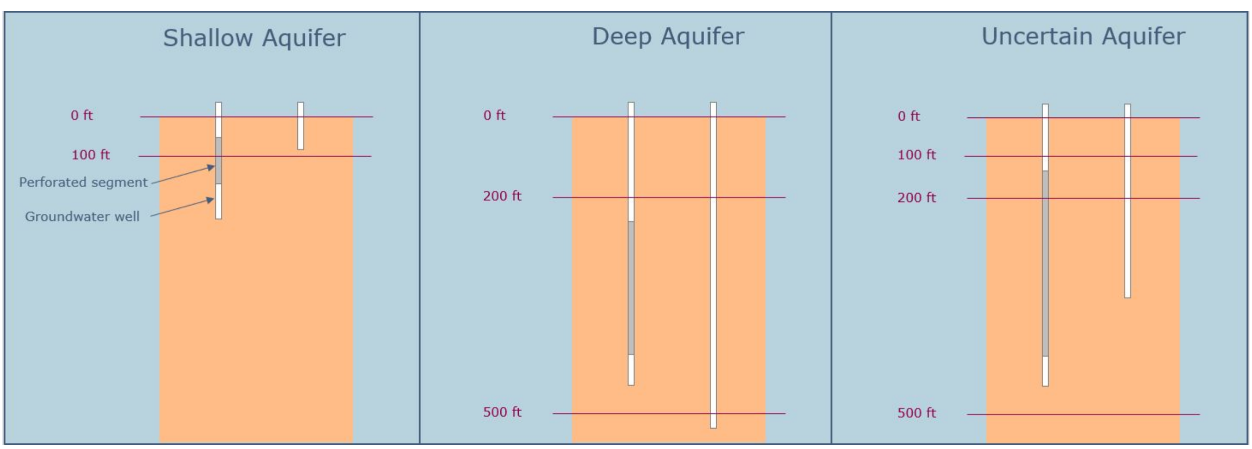

Figure 2: Groundwater well classification based on well and perforation depths.

We estimated depth to groundwater for each iGDE polygon by associating groundwater level data from nearby wells. We applied a 1 km buffer around each well and calculated the proportion of each iGDE polygon that fell within the buffered area of the well. If the majority of the polygon area fell within the buffer, we associated the well with that polygon (Figure 3, polygons A and C). Some polygons have several nearby wells, so multiple wells were associated with the polygon and the data for all nearby wells are shown in the interactive map (Figure 3, polygon B). Some polygons have long irregular shapes, so even if a well intersected the polygon but the majority of the polygon fell outside of the buffer zone for that well, it was not associated with that well (Figure 3, polygon D). Some wells are located at a different elevation than the nearby iGDE polygon. For example, a well might be located on a terrace while the iGDE polygon is in a lower elevation floodplain area. To correct for this, we calculated the average elevation for each iGDE polygon using the U.S. Geological Survey's National Elevation Dataset (NED) available on GEE (U.S. Geological Survey 2019), and used that elevation to subtract from the measured groundwater elevation from the nearby well(s) to estimate the depth to groundwater below the iGDE.

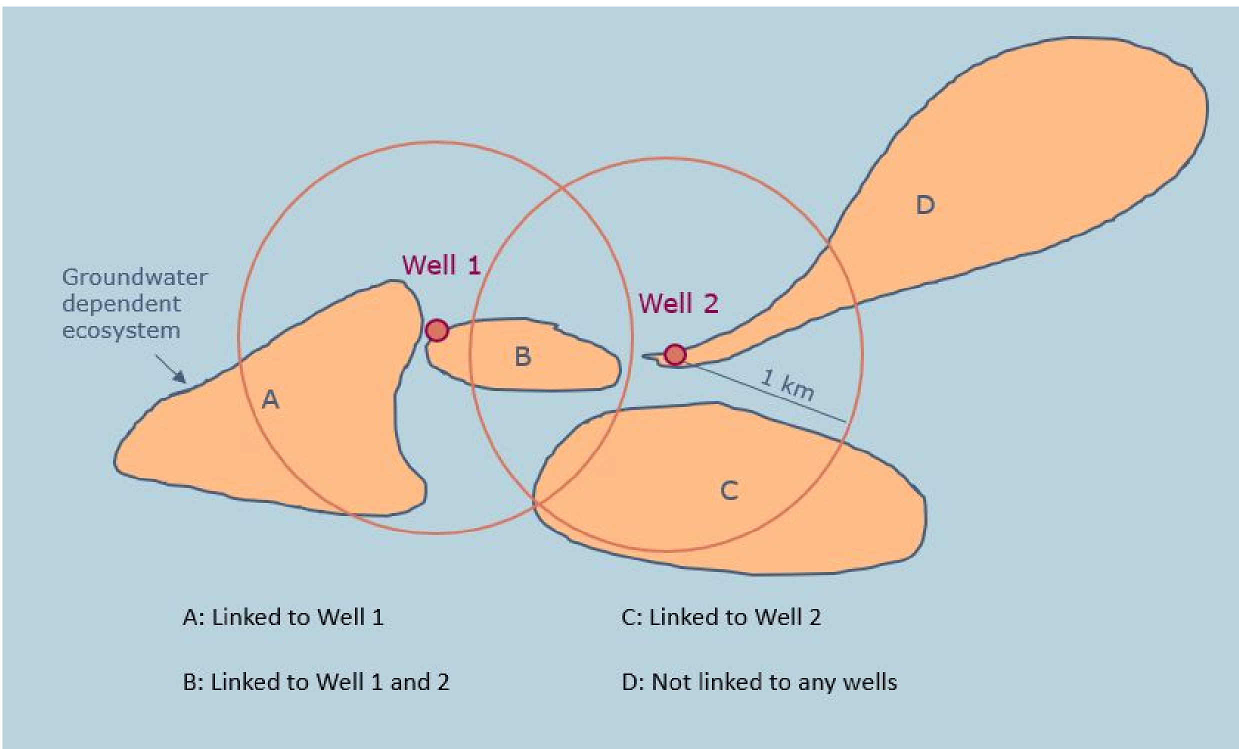

Figure 3: Example of method to link wells to groundwater dependent ecosystems.

Results

Out of the 98,275 vegetation polygons in the NC dataset, 3,942 (4%) were too small to include >50% of a landsat pixel, so no landsat data are recorded for these polygons. The landsat data summarized in 34 annual dry-month medoids was queried in Google Earth Engine for the remaining 94,333 polygons for a total of 3,207,322 potential observations (34 years * 94,333 polygons). Of those potential observations, the Landsat data was missing from 494 data points (0.02%). Most of these missing observations around found in polygons along the coast and in the Sacramento / San Joaquin delta and are likely due to dry month fog conditions and clouds. The remaining 3,206,828 data points for NDVI, NDMI, and precipitation data can be downloaded in a comma-separated-values (csv) formatted table the GDE Pulse data page. Users can also access the database API via a URL or scripting language like python or R (instructions and documentation are available for download on the GDE Pulse data page). To view charts of the data or download csv formatted tables for a single iGDE polygon, users can use the GDE Pulse interactive map.

Of the 94,333 iGDE polygons, only 16,053 (17%) have a groundwater well nearby (within 1 km) that has any groundwater level measurements since 1985. Only 5,627 (6%) of the iGDE polygons have a nearby groundwater well with sufficient information recorded to classify it as likely measuring groundwater levels in a shallow aquifer. The remaining 83% of iGDE polygons do not have any groundwater wells sufficiently close to estimate the trends in groundwater levels that may affect the health of the ecosystem. Groundwater level measurement data are available to view in the interactive map on the GDE Pulse web app. After selecting a groundwater well, users can download the measurement data in a comma-separated-value formatted table. A table that links each iGDE polygon to a well is available for download via the data page on the GDE Pulse data page. Users can also access the well measurement database API via a URL or scripting language like python or R (instructions and documentation are available for download on the GDE Pulse data page). To download the entire well measurement database, please visit the California Department of Water Resources (DWR) Periodic Groundwater Level Measurement database (https://data.cnra.ca.gov/dataset/periodic-groundwater-level-measurements). To view charts of the data or download csv formatted tables for a single groundwater well, users can use the GDE Pulse interactive map.

Discussion

Groundwater dependent ecosystems are a poorly understood yet vitally important component of the natural habitats and biodiversity in California. We found that despite having tens of thousands of groundwater wells in the state, there is insufficient data to monitor 83% of the patches of indicator vegetation for groundwater dependent ecosystems. With the passage of the Sustainable Groundwater Management Act, local groundwater sustainability agencies will be developing monitoring plans to ensure they are managing groundwater sustainably. Installing shallow groundwater monitoring wells near GDEs and reporting the data to the state CASGEM database is a vital step to improving the understanding and management of groundwater dependent ecosystems.

The GDE Pulse web app is designed to allow local groundwater managers explore the data for any iGDE polygon in the state, and compare that with trends in groundwater levels nearby if the data exist. We are currently doing an analysis of the relationship of groundwater levels and vegetation metrics statewide to find any patterns in the correlation of these two metrics of GDE health, and we will publish those results when they are available. In the meantime, we urge groundwater managers and interested stakeholders to review the data on the GDE Pulse web app to inform and improve groundwater management for healthier ecosystems.

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