Supplemental Materials

1. Santa Clara River Background

1.1 Geology

The Santa Clara River Watershed is one of the largest coastal watersheds in Southern California, spanning roughly 100 miles from the San Gabriel Mountains in Los Angeles County to the Pacific Ocean above the Oxnard Plain in Ventura County (Beller et al. 2011). It is located within the Western Transverse Ranges, west of the San Andreas Fault. The watershed as a whole is prone to high natural rates of sediment supply and high erosion rates from rapid uplift and fracturing and faulting of bedrock (Downs et al. 2013). The upper portion of the watershed is composed of older igneous and metamorphic rock, while the lower portion is made up of younger marine sedimentary rocks. The lower areas of the watershed are prone to high rates of erosion and sediment transport due to poor consolidation and a structure composed of deformed and fractured sedimentary rocks (UWCD 2021).

Within the Santa Clara River, there are groundwater basins such as the Piru Basin, Fillmore Basin, and the Santa Paula Basin. The Piru Basin is an unconfined basin about 10 miles long and 2 miles wide, consisting of alluvium deposited above thick Pleistocene deposits from the Saugus and San Pedro Formations (UWCD 2021). The alluvium is characterized by coarse sand and gravel, while deposits from the San Pedro formation consist of permeable sand and gravel (UWCD 2021). The Fillmore basin is similarly unconfined and made up of westward-sloping alluvial deposits underlain by Saugus and San Pedro Formations. It is located south of the river, stretching about 5 miles wide, and contains recent sand and gravel deposits from the Santa Clara River. The northern portion of the basin contains complex terrace deposits—south-sloping alluvium fan deposits (UWCD 2021). The Santa Paula basin is approximately 10 miles long and 4 miles wide, consisting of semi-confined, continuing thick clay deposits below alluvium deposits. It is located downstream of the Fillmore Basin and borders the Oxnard Basin (UWCD 2021).

1.2 Lithology

Other common stratigraphic units underlying the Santa Clara Basin include the Pico, Sisquoc, Monterey, Rincon, Vaqueros, Coldwater, Cozy Dell, and Jamala formations. The previously mentioned Saugus formation is Pilo-Pleistocene in age. It is nonmarine in origin, specifically fluvial transitioning to alluvial fan closer to the basin margins. It can be described as moderately-sorted, usually cross-bedded and channeled. It consists of various shades of brown interbedded sandstones and siltstones with sparse conglomerate beds/lenses (Levi & Yeats, 1993). Portions contain clay-rich lamellae and appear darker and more oxide-stained. The Pico formation is uniquely susceptible to mass wasting. Its Pliocene in age and mostly nonmarine in origin, however, certain areas indicate a marine depositional environment. It consists of conglomerate, thick to very-thick bedded sandstone, medium-bedded sandstone and mudstone, thin to very-thin bedded sandstone, siltstone, and mudstone ranging from brownish- to brownish-gray color (Rotzien et al. 2014).

The Sisquoc formation is Miocene in age and mostly marine in origin. It contains diatomaceous mudstone and shale as well as conglomerate and subordinate dolomite (Minor et al. 2009). The conglomerate beds are thick and prominent, composed of angular clasts which range from granules to boulders. Mudstone and shales are tan to white weathering gray to brown. Marine fossils are common to abundant and include fish fragments, radiolarians, sponge spicules, and molluscan shell fragments. The Coldwater formation is approximately Eocene in age, its marine in origin. It contains shallow-marine sandstone with small interbeds and thin intervals of siltstone, shale, and mudstone (Minor et al. 2009). They can be as thick as 3 meters in some areas. Sandstone is generally fine-to medium-grained, feldspathic, arkosic, silty to clayey or micaceous, and weakly cemented with calcium carbonate. Sandstones are typically gray, and yellowish-tan. Siltstone, shale, and mudstone interbeds can be as thin as 1 cm while bedded intervals can be as thick as 5 meters. The finer grained rocks of the Coldwater are generally poorly exposed due to the higher erosion when compared to the sandstone. The arrangement and distribution of these lithologies dictates regional groundwater flow and dynamics. The results of this project will be enhanced by a thorough analysis of the complexity, connectivity, and permeability of the many stratigraphic layers in the system.

1.3 Land Use

Increases in land development and urbanization can lead to various changes in streamflow discharge, ground recharge, and over water availability. This is especially critical for areas like the Santa Clara River which support various vegetation types and groundwater-dependent ecosystems. Despite increases in population growth and urbanization over the years, the Santa Clara River’s dominant land use is agriculture. Most of the urbanization and building development in this area occurred before 1985, with not much expansion since then (UWCD 2021). In the past 20 years, most changes were agricultural. The Piru and Fillmore Basins went from growing citrus to row crops, while the Fillmore and Santa Paula Basins saw major increases in avocado acreage (UWCD 2021).

1.4 Site Hydrology and Groundwater Influence

The Santa Clara River has a two-season Mediterranean climate. This climate type results in low daily mean flows in the summer, while receiving most of its precipitation during the winter months, resulting in flash flood discharges (Beller et al. 2011, Beller et al. 2016). Flow within the river is typically low and can be described as an interrupted perennial flow. The river receives most of its water from controlled releases from Lake Piru, Lake Castaic and upstream of the Piru Basin (Stillwater Sciences 2021). The major tributaries feeding into the river are Piru Creek, Sespe Creek, and the Santa Paula Creek (UWCD 2021). The interaction between surface water and groundwater is very crucial to this site, and primary groundwater recharge occurs from the percolation of surface waters of the Santa Clara River and its tributaries (Stillwater Sciences 2021). The largest discharge volumes of groundwater come from the Piru and Fillmore Basins, where the groundwater elevations are higher and the geology restricts groundwater flow, leading to groundwater upwelling (UWCD 2021).

Within the Santa Clara River watershed, groundwater plays a key role in sustaining habitat for steelhead in intermittent stretches by contributing the necessary stream flow for juvenile rearing in the summer months. Groundwater extraction has been identified as one of the major threats to the recovery of steelhead due to its ability to disconnect migratory corridors within the watershed (NMFS 2012). Steelhead recovery plans have noted that groundwater management activities and conservation releases from diversion projects influence the level of baseflow that is needed to sustain critical habitat areas. Such plans have made recommendations to align the management of groundwater extractions and conservation releases with the life-cycle of steelhead (NMFS 2012).

Stillwater Sciences has identified the Cienega and East Grove GDE Unit as study regions with high ecological value (Stillwater Sciences 2021). Both the Cienega and East Grove groundwater-dependent ecosystems support riparian plant species of interest in addition to special-status fish and bird species (Stillwater Sciences 2021). The East Grove groundwater-dependent ecosystem was selected as this project’s area of focus by Stillwater Sciences.

1.5 Riparian Vegetation

Due to the relatively low level of urban development, the Santa Clara River supports large, diverse plant communities and extensive riparian vegetation. Some of these classes of vegetation found in the river include forests, woodland, shrubland, and herbaceous (Stillwater Sciences 2021). Regions where rising groundwater is absent have minimal bank vegetation, while invasive species like *Arundo donax*—which dominates the Santa Clara River—can be found adjacent to areas with access to surface water and shallow groundwater flows (UWCD 2021). Most of the habitat in the river consists of tall grasslands and scrub vegetation, with minimal trees and groves. Dryland habitats within the region have limited tree covers and are dominated by grassland and scrub. Oaks, sycamores, and timbered areas can be found near the alluvial fan deposit of the river (Beller et al. 2011). Wetland habitat regions contain many willow brush and groves, most of which can be found near Sespe Creek (Beller et al. 2011).

1.6 Special Status Species

1.6.1 Southern Steelhead Trout

Historical evidence indicates that California Southern Steelhead Trout (*Oncorhynchus mykiss*) populations were once abundant in the major watersheds of Southern California, including the Santa Clara River with average annual runs of 9,000 (TNC 2023). However, since the beginning of the 20th century, populations have declined, with very few adult steelhead returning to the river. The steelhead first became listed as an endangered species specific to the Southern California region in 1997 and has since continued to be listed (NMFS 2012). It is understood that this decline in observed populations is likely due to factors such as flow alterations from surface water diversions, groundwater pumping, and barriers obstructing key migratory pathways in connecting tributaries (Oakley et al. 2019).

Documentation of Santa Clara River's ecological history has shed light on the major tributaries and confluences that supported high abundances of steelhead (Beller et al. 2011). These tributaries provided favorable conditions such as temperature, flow, and coverage during critical life stages (Beller et al. 2011). The Sespe, Santa Paula, and Piru Creeks have been identified as tributaries that have historically supported key ecological behaviors of the steelhead such as spawning, rearing, and migration. Prior to the construction of the Santa Felicia Dam in 1955 and the Pyramid Dam in 1970, Piru Creek supported over twenty-five miles of steelhead spawning and rearing habitat (TNC 2023). These barriers have fragmented the historical habitat of the Piru drainage and has hindered its ability to support suitable habitat for the species (Kløve et al. 2014). The Vern Freeman Diversion, located roughly 10 miles upstream of the mouth of the river, provides a fish ladder for migratory purposes (Stillwater Sciences, n.d.). The Santa Paula tributary has lost over sixty percent of its historical habitat within the river due to barriers created by natural flood occurrences (TNC 2023). This leaves Sespe Creek as the remaining undammed and unregulated major tributary for the steelhead (TNC 2023). However, it still experiences variations in flow from the watershed's dams and diversions (TNC 2023).

1.6.2 Other Species

The Santa Clara River supports a multitude of threatened and endangered species which rely on the groundwater. Some of the federally endangered bird species which rely on the groundwater-dependent ecosystems in the region include the southwestern willow flycatcher

(*Empidonax traillii extimus*) and least Bell's vireo (*Vireo bellii pusillus*) (Stillwater Sciences 2021). The California condor (*Gymnogyps californianus*) is also present in the watershed, but is not reliant on any of Santa Clara River's groundwater-dependent ecosystems (Stillwater Sciences 2021). The presence of federally endangered species mandates the protection of critical habitat—particularly groundwater-dependent ecosystems—in the watershed through the Endangered Species Act in conjunction with the requirements of the Sustainable Groundwater Management Act (USFWS, 1973; TNC 2023).

Two sensitive amphibian species—California red-legged frog (*Rana draytonii*) and arroyo toad (*Anaxyrus californicus)*—may be present in some parts of the watershed (Utom Conservation Fund, n.d.). The California red-legged frog is federally listed as a threatened species, while the arroyo toad is federally endangered (USFWS, 1994;USFWS, 1996). The unarmored threespine stickleback (*Gasterosteus aculeatus williamsoni*) is a federally endangered fish species which may be found in the upper reaches of the Santa Clara River (Utom Conservation Fund, n.d.; USFWS 2018). There is little known about the presence of these elusive species and their reliance on groundwater-dependent ecosystems. However, ecosystem restoration efforts should keep all sensitive species in mind.

1.7 Equity

The first human inhabitants of the Santa Clara River Watershed were the Chumash people (Wishtoyo Chumash Foundation 2022). There is evidence of their presence on the Central Coast stretching back thousands of years. Chumash tribes lived near the coast from San Luis Obispo all the way down to Malibu (Wishtoyo Chumash Foundation 2022). The Chumash who lived near the lower reaches of the Santa Clara River called it the *Utom*, which roughly translates to *phantom* (Utom Conservation Fund, n.d.). The name refers to the river's unpredictable flow, where water seems to come and go like a phantom or spirit (Utom Conservation Fund, n.d.). The river appears dry in the summer, but groundwater flows are usually present just beneath the surface, allowing for the success of diverse groundwater-dependent ecosystems. The shallow subsurface flows and their exchange with surface water also supported the prosperous livelihoods of the Chumash (Utom Conservation Fund, n.d.).

The Chumash people in the southern Central Coast region led rich lives with diverse diets and activities (Wishtoyo Chumash Foundation 2022). The Chumash tribe fished and hunted for much of their food, but they also relied on the local plant communities. Many of the riparian plants present in the Santa Clara River's groundwater-dependent ecosystems were vital to Chumash livelihoods, such as black cottonwood for building houses and treating bruises, chamise for making tools and weapons, common reed for thatching roofs, and goldenrod for medicine (Wishtoyo Chumash Foundation 2022; Santa Barbara Museum of Natural History 2023). The abundant ecosystems of the lower Santa Clara River allowed the Chumash to subsist in their natural environment (Wishtoyo Chumash Foundation 2022).

In California, all indigenous groups were victimized at the hands of the Padres of the Spanish Missions, and then by the U.S. government during the Gold Rush (Cordero 2015; Wolf 2017). The Chumash people—-nearly wiped out by the spread of the Missions to the Central Coast—-are one of the many California tribes whose cultures have survived against all odds (Wolf 2017). It is essential that their culture and knowledge continue to be recognized in all spaces, but particularly in environmental management. The Chumash people of the Utom watershed "...feared and respected the natural world as their greatest teacher of Traditional Knowledge" (Wishtoyo Chumash Foundation 2022). Furthermore, many Chumash have a desire to be "stewards of nature, the source of our spiritual and bodily health" (Practitioners of Nature 2011). Their deep ecological knowledge has been transferred from generation to generation, and will be necessary for future management of the sensitive habitats of the Santa Clara River. The Wishtoyo Chumash Foundation is an organization located in Ventura with goals of cultural and environmental stewardship (Wishtoyo Chumash Foundation 2022). They should be considered as a partner in the Santa Clara River Watershed Integrated Regional Watershed Management Plan.

2. Supplemental Methods

2.1 Lithology

[no additional methods]

2.2 Vertical Hydraulic Gradient

To quantify the existence and magnitude of groundwater upwelling in East Grove, we used data acquired from United Water Conservation District which contains the State Well ID, Date of Measurement, Reference Point Elevation (where the measurement was taken), Water Level Elevation (WLE), Depth to Groundwater (DTW) in feet below ground surface, coordinates (latitudes and longitudes), and the well depths (ft) for a nested monitoring well that contains 4 wells screened at different intervals within the same borehole. **Table 2.2a** provides the different well specifications at the nested monitoring well site. For the purpose of the vertical hydraulic gradient analysis, only the wells with a 100 ft (Well ID: 03N20W08B07S) and 530 ft (Well ID: 03N20W08B04S) total well depth were used.

Table 2.2a. Well attributes for the UWCD Nested Monitoring Wells in East Grove

Well ID	**RP**	**Lat.**	**Long.**	**Well Depth (ft)**	**Comments**
03N20W08B04S	315.24	34.3623453	-118.9963953	530	East Grove Site, FPBGSA

					nested monitoring well 530
03N20W08B 05S	315.24	34.3623453	-118.9963953	400	East Grove Site, FPBGSA nested monitoring well 400
03N20W08B 06S	315.24	34.3623453	-118.9963953	220	East Grove Site, FPBGSA nested monitoring well 220
03N20W08B 07S	315.24	34.3623453	-118.9963953	100	East Grove Site, FPBGSA nested monitoring well 100

Table 2.2b. Nested Monitoring Well Data — DTG recorded measurements for deep well (530 feet)

State Well ID	Date of Measurement	DTG	WLE	Well Depth (ft.)	Well Top Perf. (ft.)	Well Bottom Perf. (ft.)
03N20W08B04S	11/16/2022	9.06	306.18	530	490	530
03N20W08B04S	1/25/2023	2.81	312.43	530	490	530
03N20W08B04S	2/8/2023	2.11	313.13	530	490	530
03N20W08B04S	3/20/2023	0.45	314.79	530	490	530
03N20W08B04S	5/3/2023	1.55	313.69	530	490	530
03N20W08B04S	5/8/2023	1.06	314.18	530	490	530
03N20W08B04S	7/17/2023	2.35	312.89	530	490	530
03N20W08B04S	9/11/2023	2.99	312.25	530	490	530

03N20W08B04S	10/11/2023	3.21	312.03	530	490	530
03N20W08B04S	10/23/2023	2.44	312.80	530	490	530

Table 2.2b. Table of all recorded measurements taken at the deepest well at the nested monitoring well site. DTG is the depth-to-groundwater, measured in feet below ground ground surface. WLE is the Water Level Elevation in feet above sea level. Well Depth (ft.) is the total well depth in feet below ground surface. Well Top Perf. (ft.) is the top of the screened interval of the well. Well Bottom Perf. (ft.) is the bottom of the screened interval of the well.

Table 2.2c. Nested Monitoring Well Data — DTG recorded measurements for shallow well (100 feet)

State Well ID	Date of Measurement	DTG	WLE	Well Depth (ft.)	Well Top Perf. (ft.)	Well Bottom Perf. (ft.)
03N20W08B07S	11/16/2022	5.18	310.06	100	60	100
03N20W08B07S	1/25/2023	1.98	313.26	100	60	100
03N20W08B07S	2/8/2023	2.92	312.32	100	60	100
03N20W08B07S	3/20/2023	1.53	313.71	100	60	100
03N20W08B07S	5/3/2023	2.35	312.89	100	60	100
03N20W08B07S	5/8/2023	2.25	312.99	100	60	100
03N20W08B07S	7/17/2023	2.99	312.25	100	60	100
03N20W08B07S	9/11/2023	3.62	311.62	100	60	100
03N20W08B07S	10/11/2023	3.71	311.53	100	60	100
03N20W08B07S	10/23/2023	3.24	312.00	100	60	100

Table 2.2c. Table of all recorded measurements taken at the shallow-most well at the nested monitoring well site. DTG is the depth-to-groundwater, measured in feet below ground ground surface. WLE is the Water Level Elevation in feet above sea level. Well Depth (ft.) is the total well depth in feet below ground surface. Well Top Perf. (ft.) is the top of the screened interval of the well. Well Bottom Perf. (ft.) is the bottom of the screened interval of the well.

The well development process for the East Grove nested monitoring well was completed in November of 2022. The first measurements were recorded on or around the date of well development (November 2022). The last recorded measurement of the two wells was on 10/23/2023. Since the well development phase was completed in late 2022, the 2023 water level measurements were used to assess changes in water levels.

To assess the vertical hydraulic gradient, the depth to groundwater measurements were used to find the changes in hydraulic head, denoted by Δh, where the hydraulic head is a measurement of the potential energy of the groundwater at a specific point. To find the change in vertical distance between the two wells, we used the difference between the total well depths of the two wells (100 ft and 530 ft respectively). This change in vertical distance is denoted by Δz.

The equation for determining the vertical hydraulic gradient is Δh/Δz, where Δh is calculated by the depth to groundwater measurement (DTG) of the 100 ft well subtracted to the DTG measurement of the 530 ft well at a certain date, and Δz is calculated by taking the the total well depth of the shallowest well (100 ft) and subtracting the total well depth from a deeper well (530 ft).

Using this equation, we calculated the Δh for each of the 10 recorded measurements and calculated a Δz value of -430 (100ft - 530 ft). Table 2.2d, below, contains the date of measurements, each calculated Δh value, Δz, and Δh/Δz (vertical hydraulic gradient).

Date of Measurement	Δh	ΔZ	Δh/Δz
11/16/2022	-3.88	-430	0.009023257189
1/25/2023	-0.83	-430	0.001930232381
2/8/2023	0.81	-430	-0.001883721352
3/20/2023	1.08	-430	-0.002511627868
5/3/2023	0.80	-430	-0.001860465005
5/8/2023	1.19	-430	-0.002767441994
7/17/2023	0.64	-430	-0.001488372337
9/11/2023	0.63	-430	-0.001465115991
10/11/2023	0.50	-430	-0.001162790698
10/23/2023	0.80	-430	-0.001860465005

Table 2.2d. Vertical hydraulic gradient calculations of a shallow (100 ft) and deep (530 ft) well in East Grove.

2.3 Hydrology

2.3.1 Data Acquisition

A. East Grove Shallow Groundwater Monitoring Wells

In late 2015, shallow groundwater monitoring wells were installed in the Santa Clara River watershed by a UCSB research team consisting of Adam Lambert and other Marine Science Institute researchers. Our team received depth-to-groundwater data from these shallow groundwater monitoring wells from measurements taken approximately once a month from December 2015 to March 2023. This data was then filtered to exclude wells outside of the East Grove, using a Geographic Information System Area-of-Interest received from the RIVR Lab at UCSB.

There are 21 UCSB wells within East Grove with depth-to-groundwater data, as shown in Figure 2.1.1a. Within East Grove, there are 2 wells on Taylor Ranch (referred to as Taylor 1 and 2), 9 wells in the Hedrick Ranch Preserve (referred to as HRP 1-9), and 10 wells located in the Ventura County Watershed Protection District (referred to as VCWPD 1-10).

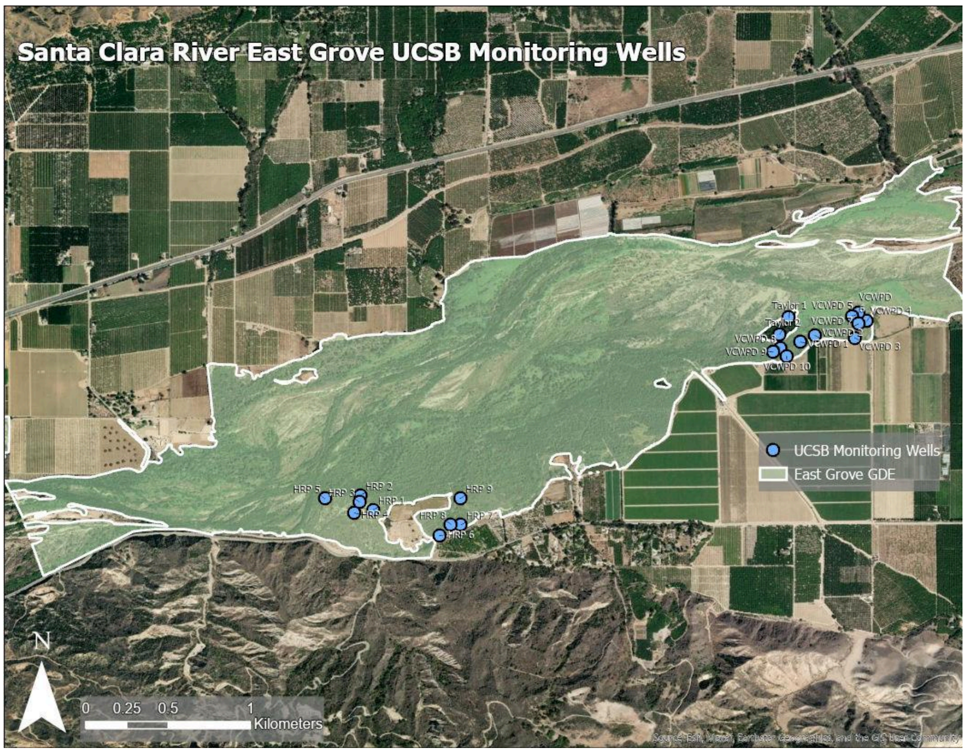


Figure 2.1.1a. UCSB shallow groundwater monitoring well locations within the East Grove region of the Santa Clara River (HRP 1-9, Taylor 1 and 2, VCWPD 1-10).

The data received for each well included latitude, longitude, well elevation, height of well lip (measured in 2015 2017, and 2019), total well depth, and depth-to-groundwater measurements for each date of measurement. We then simplified the data to include latitude, longitude, date of measurement, and depth-to-groundwater at each measurement for further analysis. When the UCSB team noted “no water,” the depth-to-groundwater was changed to the total well depth to account for the uncertainty of depth-to-groundwater in dry periods.

We looked to the nearest meteorological station to our East Grove study site to obtain relevant precipitation data for our study’s time series and recharge analysis. We found a nearby Santa Paula CIMIS station that was missing measurements from 2015 to 2023 (DWR 2023). To obtain complete precipitation data for the study area region, modeled daily and monthly precipitation data was downloaded from PRISM from 2010 to 2023 (PRISM Climate Group 2023). The nearest meteorology station to East Grove—the Santa Paula CIMIS station—has missing and sporadic data for many years in the study period (2015-2023) (DWR 2023). The downloaded precipitation data from PRISM was representative of the coordinates 34.6644, -119.0304 (PRISM Climate Group 2023). Using the data that was available from the CIMIS station, we completed a Pearson correlation analysis between the PRISM and CIMIS data to verify that the modeled PRISM results were a valid replacement. We found that results were highly correlated for the timestamps in which both PRISM and CIMIS had monthly precipitation measurements, with a Pearson correlation of 0.928 (Figure 2.1.1b). Thus, it was appropriate to use the PRISM-modeled precipitation as a replacement for actual precipitation measurements. In R, we calculated PRISM's total monthly precipitation values' mean and standard deviation during the study period. Using these numbers, we included months where total precipitation was greater than one standard deviation above mean monthly precipitation as "High Precipitation Intervals".

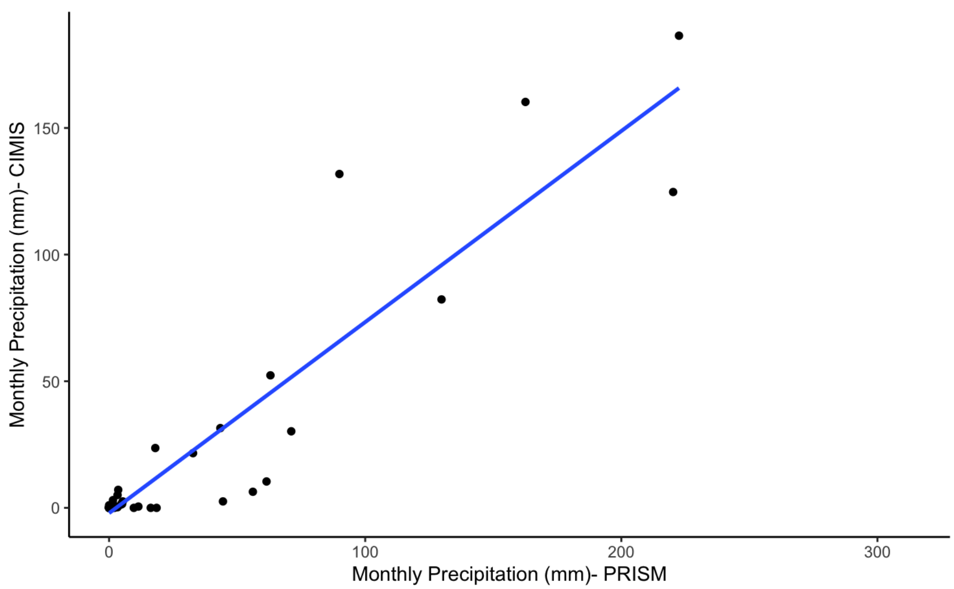


Figure 2.1.1b. Correlation between CIMIS station measurements and PRISM modeled daily precipitation (Pearson's r=0.928).

B. Fillmore Subbasin Wells

Groundwater level data for deeper wells was pulled from the Department of Water Resources (DWR)' SGMA Data Viewer web tool. The web tool provides groundwater-related datasets under the spatial extent of the State of California (DWR 2023). The groundwater-related datasets contain collections of groundwater level data at different spatial and temporal extents. The groundwater level and groundwater wells information is a collection of data from the following cooperating agencies:

I. Data collected through the CASGEM (California Statewide Groundwater Elevation Monitoring) Program;
II. The California Natural Resources Agency Open Data Platform (https://data.cnra.ca.gov/);
III. The Water Data Library (https://wdl.water.ca.gov/waterdatalibrary/)
IV. Sustainable Groundwater Management Act (SGMA) Portals Monitoring Network

The web tool's water level dataset includes groundwater level measurements that were taken manually twice per year (to capture the peak high and low values in groundwater elevations), or taken on a more frequent basis (monthly, weekly, daily). Daily measurements come from the DWR's automated monitoring network of groundwater sites.

To obtain relevant historical groundwater level data near our specific area of interest (the East Grove GDE), periodic and continuous water level measurements wells were filtered to the spatial extent of the Fillmore Subbasin. This filtering step produced a total of 81 active wells. We did not filter for wells with a specific use (irrigation, industrial, observation, public supply, residential, other, and unknown wells), so the 81 wells ranged from observation to production wells (i.e., irrigation, residential, and public supply).

We then downloaded the wells and water level data in bulk for the 81 wells in the Fillmore Subbasin. The raw downloaded data can be found in the project's shared Google Drive folder, "Raw Data - SGMA Data Viewer" and the raw zip file is called "Query_Result_559952799307774". The raw downloaded zip folder contains a series of different well attributes and water level data information such as site_code, well perforations, well coordinates, well use, well type, well owner, date of measurement, reference point elevation, ground surface elevation, in feet, using NAVD88, ground surface elevation to water surface elevation in feet (GSE_WSE), etc.

Data Filtering & Cleaning

Goal*: Find wells that contain data within the time period of 2010 to 2023*

The "._GroundwaterElevation.csv" and the "._Stations.csv" files from the full query download were opened in Excel spreadsheets. To make the data accessible to all student members of the project, the files were copied into two different tabs on a google spreadsheet—one tab hosting the groundwater level records (from the ._GroundwaterElevation.csv file) and one tab to host the well station information (from the ._Stations.csv file). The station's csv contained parameters that were needed to make sense of the groundwater level measurements. The "=VLOOKUP" formula was used to bring relevant well information into the groundwater level measurement data tab, using the site codes for each well as the unique identifier in the formula. The well station attributes that were pulled over included:

I. Coordinates of each of the wells (latitude and longitude)
II. Well use

III. Well type
IV. Well depth
V. Top and bottom perforation measurement (TOP_PRF & BOT_PRF)
VI. Ground surface elevation (GSE)
VII. Reference point elevation (RPE)

A copy of the data was made and moved to a separate google drive folder called "All Fill Wells - Data from 2010 - 2023". Using this copy of the spreadsheet, called Fillmore_Wells_Data_2010 to 2023 we placed filters on all columns and filtered the "MSMT_DATE" column from A to Z. We then deleted any rows that contained data prior to 2010. We then filtered the "GSE_WSE" column, which is the column that provided the depth to groundwater level (in feet) data, from A to Z. To obtain accurate results in our pivot tables (see the Data Filtering by Count of Measurements subsection below), the rows whose cells did not have any GSE_WSE recorded were deleted. At this point, we were left with a total of ***39*** wells in the Fillmore sub basin that had at least one depth-to-groundwater level measurements recorded during the years 2010 through 2023.

Data Filtering: Count of Measurements Per Year

Goal*: Find the number of measurements taken each year for each well during 2010 through 2023 using pivot tables and "COUNT" and "COUNTIFs" formulas*

We created a copy of the Fillmore_Wells_Data_2010 to 2023 spreadsheet, titled it "Fill Wells - # of Measurements by Year [2010 to 2023]" and placed it in a new shared google drive folder called # of Measurements Per Year [2010 - 2023]. The following wells were removed since these wells are included in the shallow groundwater monitoring wells analysis:

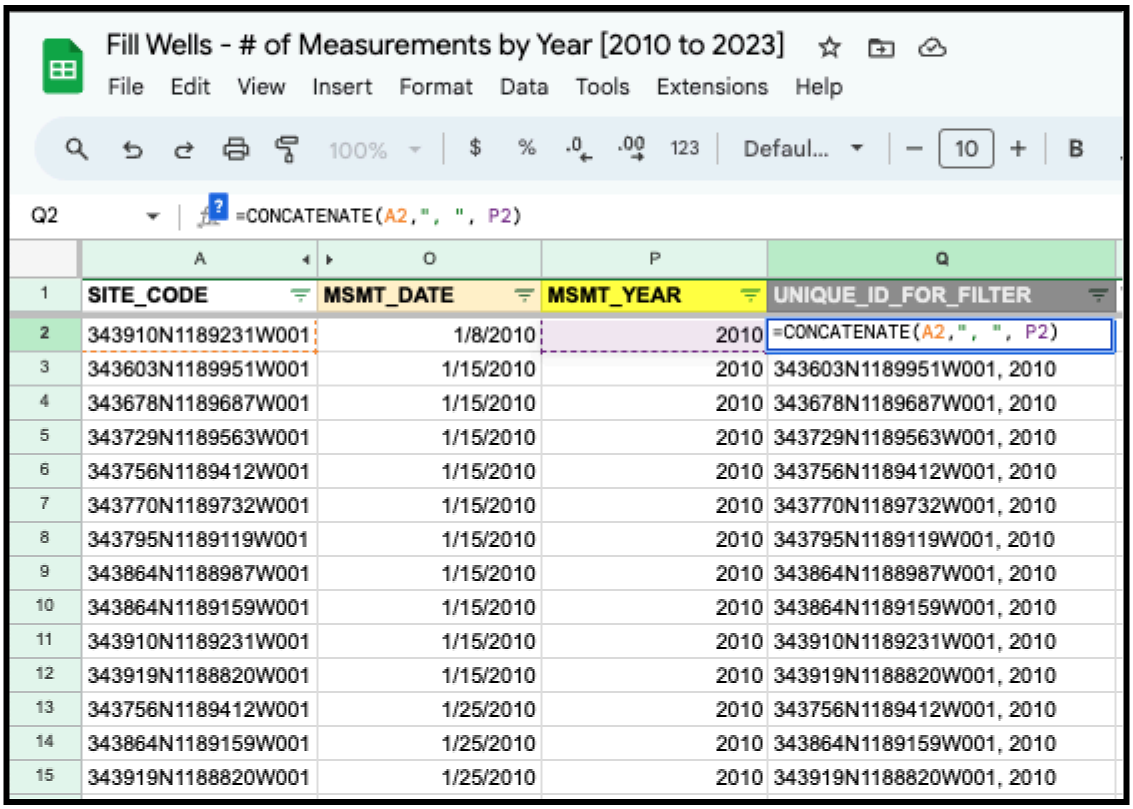
I. SITE_CODE: 343639N1189918W001
   A. Well_Name: 03N20W08VCWPD8 and
   B. Well name used in shallow groundwater analysis: HRP9
II. SITE_CODE: 343556N1190092W001
   A. Well_Name: 03N20W07HRP9
   B. Well name used in shallow groundwater analysis: VCWPD8

To observe how many measurements were recorded each year for each well, we created a new unique identifier for each row to include the well site code and the respective year for that row's measurement. To do this, the following steps were taken:

1. Highlight the "MSMT_DATE" column (column that includes the month, day, year, and time the respective measurement was taken) and change the value type to "short date" so that only the month, day, and year values are reported and not the time of record
2. Create three new columns to the right of the "MSMT_DATE" column
3. Copy the values from the MSMT_DATE in the empty column to the right of it

4. Highlight the entire column, go to the ribbon bar, select Data, then Text to Columns
    a. For the separator identifier, select the custom option and use the "/" symbol as the custom separator
    b. The three columns are populated with the month, day, and year among the three respective columns
    c. The column that contained just the year was given a column header "MSMT_YEAR" and the columns that contained the month and day were deleted

After separating out the year from each record date, we created a new unique identifier by using the `=CONCATENATE' function, using the values under the SITE_CODE column and the MSMT_YEAR column. Figure 2.2.1a below is a screenshot of the spreadsheet representing what the new unique IDs (called UNIQUE_ID_FOR_FILTER) looks like after completing these steps.



	A	O	P	Q
1	SITE_CODE	MSMT_DATE	MSMT_YEAR	UNIQUE_ID_FOR_FILTER
2	343910N1189231W001	1/8/2010	2010	=CONCATENATE(A2,", ", P2)
3	343603N1189951W001	1/15/2010	2010	343603N1189951W001, 2010
4	343678N1189687W001	1/15/2010	2010	343678N1189687W001, 2010
5	343729N1189563W001	1/15/2010	2010	343729N1189563W001, 2010
6	343756N1189412W001	1/15/2010	2010	343756N1189412W001, 2010
7	343770N1189732W001	1/15/2010	2010	343770N1189732W001, 2010
8	343795N1189119W001	1/15/2010	2010	343795N1189119W001, 2010
9	343864N1188987W001	1/15/2010	2010	343864N1188987W001, 2010
10	343864N1189159W001	1/15/2010	2010	343864N1189159W001, 2010
11	343910N1189231W001	1/15/2010	2010	343910N1189231W001, 2010
12	343919N1188820W001	1/15/2010	2010	343919N1188820W001, 2010
13	343756N1189412W001	1/25/2010	2010	343756N1189412W001, 2010
14	343864N1189159W001	1/25/2010	2010	343864N1189159W001, 2010
15	343919N1188820W001	1/25/2010	2010	343919N1188820W001, 2010

Figure 2.2.1a. Creation of the "UNIQUE_ID_FOR_FILTER" column

A new tab on the spreadsheet was created and called *Count # of measurements Per Yr* and the values in the UNIQUE_ID_FOR_FILTER column were copied over. We then removed any duplicates from the UNIQUE_ID_FOR_FILTER column, highlighted the column, and made a copy of the column values to the right of it. We then used the split text to columns feature in the ribbon bar so that the site codes and years were separated into two different columns. To the right of these two columns, a new column called "Measurements in Year" was created. In this column, we used the `=COUNTIF' function to count how many times each unique value in the UNIQUE_ID_FOR_FILTER column was counted.

A pivot table was created in a new tab that contained the following data from the *Count # of measurements Per Yr* tab:

1. Rows: SPLIT_TEXT_TO_COLUMNS_YEARS
2. Columns: SPLIT_TEXT_TO_COLUMNS_SITE_CODE
3. Values: Measurements in Year

Under the newly created pivot table, a sequence of rows were titled: Unique Count of Year, CONTF_GRTR_3, CONTF_GRTR_4, CONTF_GRTR_5, CONTF_GRTR_6, CONTF_GRTR_7, CONTF_GRTR_8, CONTF_GRTR_9, and CONTF_GRTR_10. For each of these rows, we used a series of formulas, namely the =COUNT and =COUNTIF functions. For each of these rows, a series of formulas was used, namely the =COUNT, and =COUNTIF functions. The range used for each of the `=COUNTIF' functions looked to the "Measurements in a Year" values in the pivot table for each of the wells. The following breaks down the different row headers, the formulas used for each, and a general description of what the formula means:

1. Unique Count of Year
    a. =COUNT(C4:C17)
        i. Formula is counting how many years of data there is during 2010 to 2023, with 14 being the maximum count.
2. CONTF_GRTR_3
    a. =COUNTIF(C4:C17,">3")
        i. Count the number of years that had more than 3 recorded measurements (during the time period of 2010 to 2023).
3. CONTF_GRTR_4
    a. =COUNTIF(C4:C17,">4")
        i. Count the number of years that had more than 4 recorded measurements (during the time period of 2010 to 2023).
4. CONTF_GRTR_5
    a. =COUNTIF(C4:C17,">5")
        i. Count the number of years that had more than 5 recorded measurements (during the time period of 2010 to 2023).
5. CONTF_GRTR_6
    a. =COUNTIF(C4:C17,">6")
        i. Count the number of years that had more than 6 recorded measurements (during the time period of 2010 to 2023).
6. CONTF_GRTR_7
    a. =COUNTIF(C4:C17,">7")

i. Count the number of years that had more than 7 recorded measurements (during the time period of 2010 to 2023).

7. CONTF_GRTR_8
    a. =COUNTIF(C4:C17,">8")
        i. Count the number of years that had more than 8 recorded measurements (during the time period of 2010 to 2023).
8. CONTF_GRTR_9
    a. =COUNTIF(C4:C17,">9")
        i. Count the number of years that had more than 9 recorded measurements (during the time period of 2010 to 2023).
9. CONTF_GRTR_10
    a. =COUNTIF(C4:C17,">10")
        i. Count the number of years that had more than 10 recorded measurements (during the time period of 2010 to 2023).

After completing these functions for the first well in the pivot table (the well whose values corresponded to the "C4:C17" range in the functions above), the formula was dragged across to populate all "COUNTIF" values for all wells in the pivot table.

We then created a new tab and called it "transpose_for_attributes". In this tab, we used the `=TRANSPOSE' function to pull over the corresponding values for each of the "CONTF_GRTR_" headers. Figure 2.2.1b represents what this formatted table looks like.

SITE_CODE	*Unique Count of Yea*	CONTF_GRTR_3	CONTF_GRTR_4	CONTF_GRTR_5	CONTF_GRTR_6	CONTF_GRTR_7	CONTF_GRTR_8	CONTF_GRTR_9	CONTF_GRTR_10
343561N1190356W001	14	9	1	1	0	0	0	0	0
343599N1190280W001	11	6	4	2	1	0	0	0	0
343603N1189951W001	14	14	14	14	13	13	13	13	13
343614N1190290W001	14	13	13	13	5	0	0	0	0
343625N1190323W001	12	11	8	6	4	2	0	0	0
343639N1189870W001	12	1	0	0	0	0	0	0	0
343644N1189467W001	14	10	1	0	0	0	0	0	0
343678N1189687W001	14	12	10	5	3	0	0	0	0
343696N1189574W001	9	6	6	5	2	0	0	0	0
343729N1189563W001	11	7	6	5	4	2	0	0	0
343753N1190062W001	14	12	1	1	0	0	0	0	0
343756N1189412W001	14	14	14	14	14	14	14	14	14
343763N1190076W001	14	9	6	6	4	0	0	0	0
343767N1190215W001	8	2	2	0	0	0	0	0	0
343770N1189732W001	7	4	2	1	1	0	0	0	0
343783N1189178W001	14	6	1	1	0	0	0	0	0
343789N1189312W001	14	13	1	1	0	0	0	0	0
343795N1189119W001	13	8	1	1	0	0	0	0	0
343811N1189034W001	13	2	0	0	0	0	0	0	0
343829N1190196W001	9	7	7	7	3	0	0	0	0
343860N1190096W001	8	1	0	0	0	0	0	0	0
343864N1188987W001	11	1	1	1	1	1	1	1	0
343864N1189159W001	14	14	14	13	12	9	6	5	4
343891N1190120W001	3	1	0	0	0	0	0	0	0
343900N1189831W001	14	10	8	5	2	1	1	0	0
343910N1189231W001	13	12	12	12	11	10	10	9	6
343912N1188910W001	5	1	1	0	0	0	0	0	0
343917N1188823W001	13	12	10	9	8	6	6	5	5
343919N1188820W001	14	13	13	12	12	9	8	6	6
343986N1189487W001	12	11	10	10	3	0	0	0	0
344047N1189281W001	11	7	6	6	4	0	0	0	0
344056N1189195W001	14	11	9	5	3	2	0	0	0
344069N1189490W001	14	11	1	1	0	0	0	0	0
344083N1189691W001	8	5	2	0	0	0	0	0	0
344083N1189701W001	8	5	1	0	0	0	0	0	0
344086N1189512W001	9	9	9	9	8	8	8	8	8
344106N1189272W002	13	9	7	6	4	1	0	0	0
344106N1189431W001	14	9	5	5	3	3	3	3	3
344195N1189306W001	14	14	14	13	13	9	9	7	4

Figure 2.2.1b. Formatted Pivot Table Data for all DWR wells in the SGMA Data Viewer, with all COUNT_IF Values shown.

Setting Thresholds for Data Robustness

Goal: Utilize the output from the Pivot Table data to identify and categorize wells with sufficient to suboptimal measurement data essential for conducting thorough time-series and recharge analyses.

To categorize wells based on the quality of their data, with the 'quality' being defined by the number of measurements taken each year for each well, we established a standardized threshold. Using a standardized approach, we looked to each of the CONTF_GRTR_ columns and used the columns' corresponding values to identity wells that fit the following criteria:

I. Criteria:
   A. **BEST**:
      1. Wells that have 10 or more measurements per year over a course of at least 9 years during the time period of 2010 to 2023
      2. ***Data Used***: "CONTF_GRTR_9" and "CONTF_GRTR_10" columns whose values are 9 or greater
   B. GOOD:
      1. Wells that have 8 or 9 measurements per year over a course of at least 9 years during the time period 2010 to 2023
      2. ***Data Used***: "CONTF_GRTR_8" to "CONTF_GRTR_7" columns whose values are 9 or greater
   C. OKAY:
      1. Wells that have 6 or 7 measurements per year over the course of at least 9 years during the time period of 2010 to 2023
      2. ***Data Used:*** "CONTF_GRTR_6" to "CONTF_GRTR_5" columns whose values are 9 or greater
   D. POOR:
      1. Wells that have 3 or 4 measurements per year over the course of at least 9 years during the time period of 2010 to 2023
      2. ***Data Used***: "CONTF_GRTR_4" to "CONTF_GRTR_3" columns whose values are 9 or greater

Utilizing this threshold and criteria methods, we found that 22 out of the 39 wells filled these different criteria. We organized each well by the category they fit into (i.e., Best, Good, Okay, Poor). To make further analysis easier to interpret and establish a more relevant name for each of these 22 wells, a new internal id was created for each well:

I. Fill 1 - Fill 3 = "Best"
II. Fill 4 - Fill 6 = "Good"
III. Fill 7 - Fill 10 = "Okay"
IV. Fill 11 - Fill 22 = "Poor"

After naming each of the wells, the `=VLOOKUP' formula was used to bring over the corresponding internal id in the spreadsheet's tab that contained the well measurement data, and matched the new internal ids based on the original "SITE_CODE" IDs for each well. To have this data prepared for the mapping, time series, and recharge analysis, we created 4 individual spreadsheets (one Best, Good, Okay, and one Poor) with each spreadsheet containing a separate tab of data for each well (Fill 1, Fill 2, Fill 3, etc.).

2.3.2 Time-Series Plots

With data on depth-to-groundwater and precipitation, time-series graphs were created using the "ggplot" package in R for each of the 21 wells located within East Grove. Each of these graphs have dates on the x-axes and depth-to-groundwater in centimeters on the left y-axes. The graph is reversed so that ground level is shown at the top in black, and total well depth is near the bottom in red. The right y-axes have daily precipitation in millimeters. Depth-to-groundwater measurements as taken by the UCSB team are shown with connected black dots corresponding to measurement dates on the x-axis and depths in centimeters on the left y-axis. Dates with no depth-to-groundwater measurements, indicated by notes of "no water," are represented by gray vertical lines below total well depth to represent uncertainty in the actual depth-to-groundwater. If a well is dry, depth-to-groundwater must be below the total depth of the well, so the true measurement cannot be known.

Daily precipitation values in millimeters are shown as light blue lines coming from the top of the graph, corresponding to dates on the x-axis and estimates of precipitation in millimeters on the right y-axis. Finally, "high precipitation intervals" are indicated with gray-blue rectangles corresponding to the months with higher than average precipitation (mean + 1 standard deviation) on the x-axis.

2.3.3 Water-Level Rise Analysis

Least-squares regression is often the default method for completing analyses of linear regression. However, when quantitative data contains outliers, there are more accurate methods for computing regressions. These are considered "robust regressions," and include methods such as Theil-Sen, L_1 and L_2, and iteratively reweighted least squares (Pennsylvania State University 2023). Theil-Sen regression was chosen for this study because it is particularly resistant to outliers and "odd data" (Goldstein-Greenwood 2023).

Theil first developed his method of regression to perform regression analysis using the medians between two points, rather than means, in 1950 (Goldstein-Greenwood 2023). Sen changed the method to omit infinite slopes in 1968 (Goldstein-Greenwood 2023). Theil-Sen regression is a powerful tool in statistical analysis because it can correct for unusual data, particularly in the case of extreme outliers (Goldstein-Greenwood 2023). The method is described as follows:

1. Slope is calculated between every pair of points in the data set as shown below:

$$m_i^j = (y_j - y_i)/(x_j - x_i)$$

$$\ldots$$

2. The Theil-Sen regression slope is the median of the slopes between each pair of points.

$$m = \text{median}\{m_i^j, m_j^k, m_k^l, \ldots\}$$

3. The y-intercept (b) is calculated by plugging in the values of each data point into the equation with the median slope.

$$y_i = m(x_i) + b_i$$

$$b_i = m(x_i) - y_i$$

$$\ldots$$

4. The median of all y-intercepts is the Theil-Sen regression intercept.

$$b = \text{median}\{b_i, b_j, b_k, \ldots\}$$

This method results in an estimate of linear regression with one slope and one y-intercept.

Using the median instead of the mean resists the impact of outliers (Goldstein-Greenwood 2023). For example, in the data set {1,2,3,4,5} {2,4,6,8,10}, the mean and median slopes are both equal to 2. However, if the final data point is changed from (5,10) to (10,100), the mean slope would be 7.78, while the median slope would remain at 2. Thus, Theil-Sen regression is more likely than least-squares linear regression to estimate the true nature of a data set (Goldstein-Greenwood 2023).

We used Theil-Sen regression to estimate recharge ratios for all UCSB shallow groundwater monitoring wells. The previously described methods on the water-table fluctuation method resulted in a data frame containing information for all wells. The well data frames had data points corresponding to each recharge event, with information on the timing, water-level rise, and total precipitation. We used R to run Theil-Sen models between precipitation and water-level rise (dH).

The Theil-Sen models estimated dH/precipitation ratios using precipitation as the controlling factor. They resulted in estimates of slopes and y-intercepts for each well's recharge events, with corresponding p-values. Using R's ggplot package, we used the Theil-Sen models to add regression lines to scatter plots for each well. This allowed us to visualize the impact of precipitation on recharge. The differing recharge and water-level rise/precipitation ratios of all the UCSB monitoring wells were used to generate maps in ArcGIS.

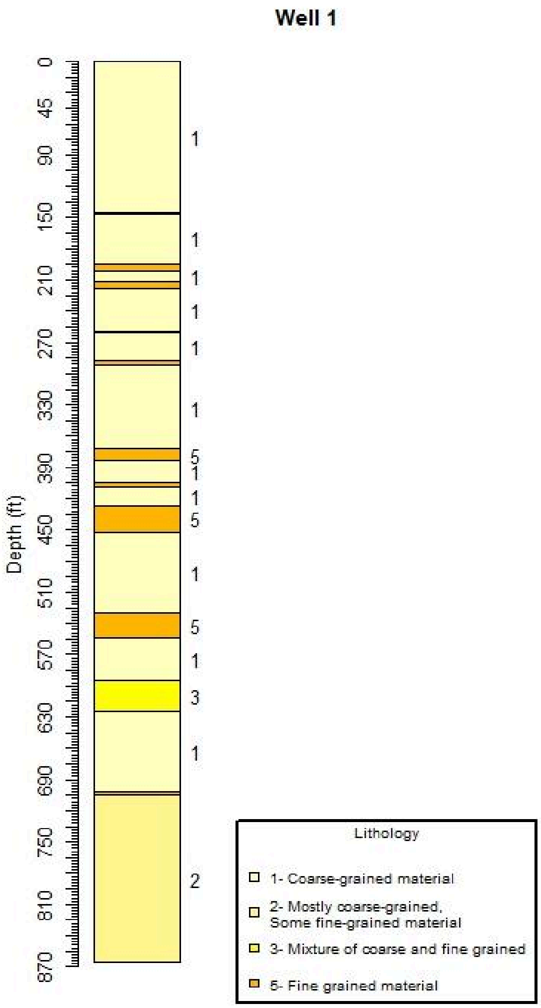
3. Supplemental Results

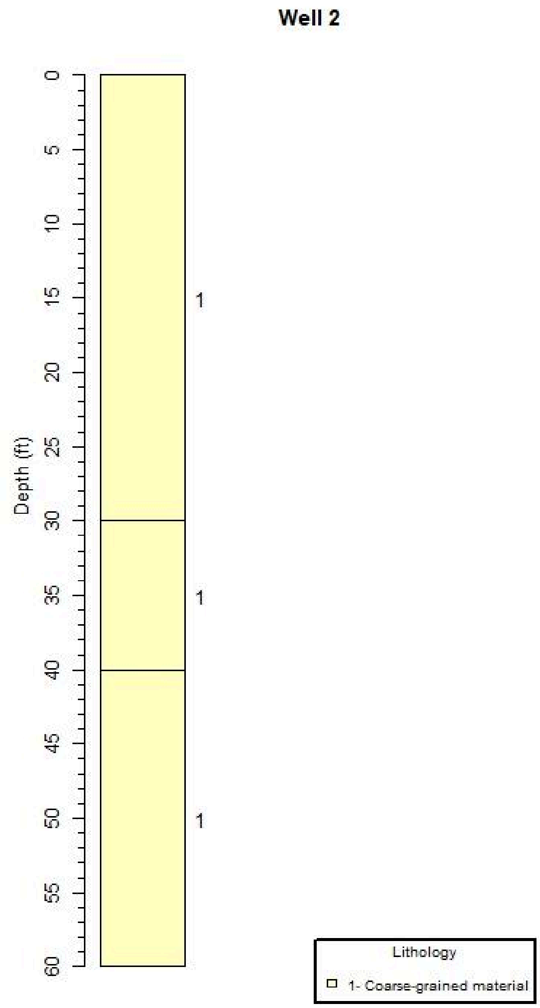
3.1 Lithology

Each of the wells were individually plotted with the corresponding lithologies per depth in using the StratigrapheR package. Each well plot contains the wells depth on the y-axis along with the corresponding category id on the left side of each of the wells. Table 3.1.2 contains the corresponding well completion reports with the well id.

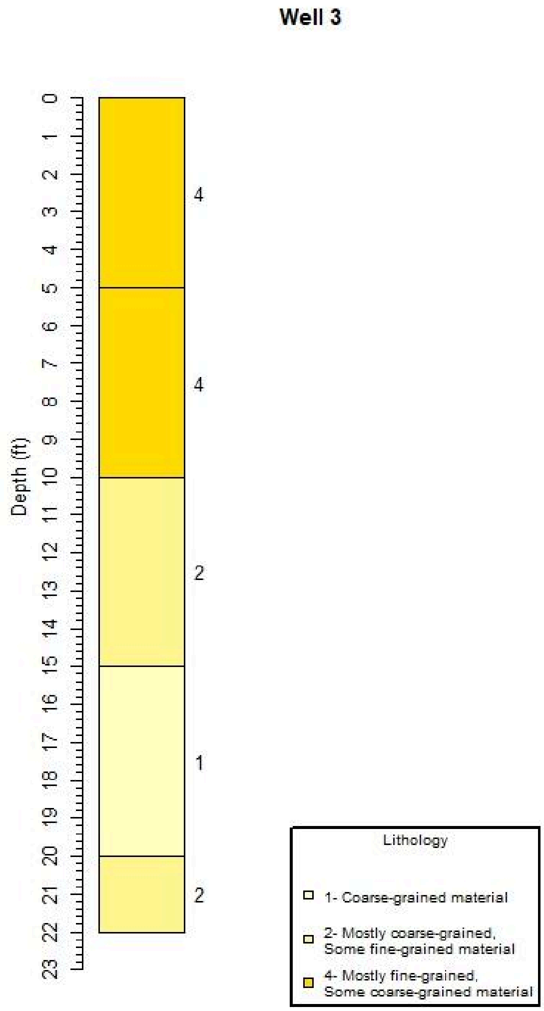
3.1.1 Well Plots

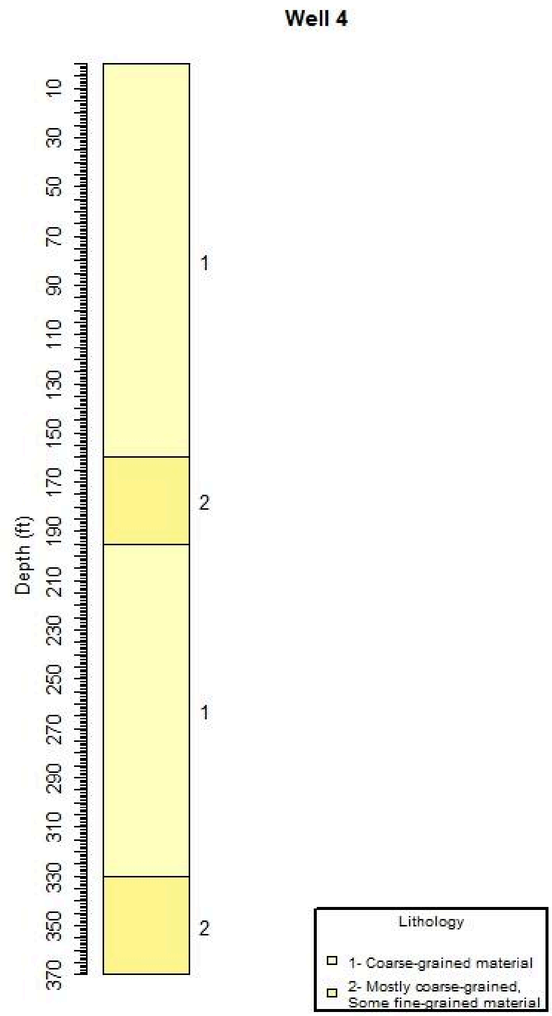
Well 1 (WCR2004-015336) & Well 2 (WCR2001-015789)



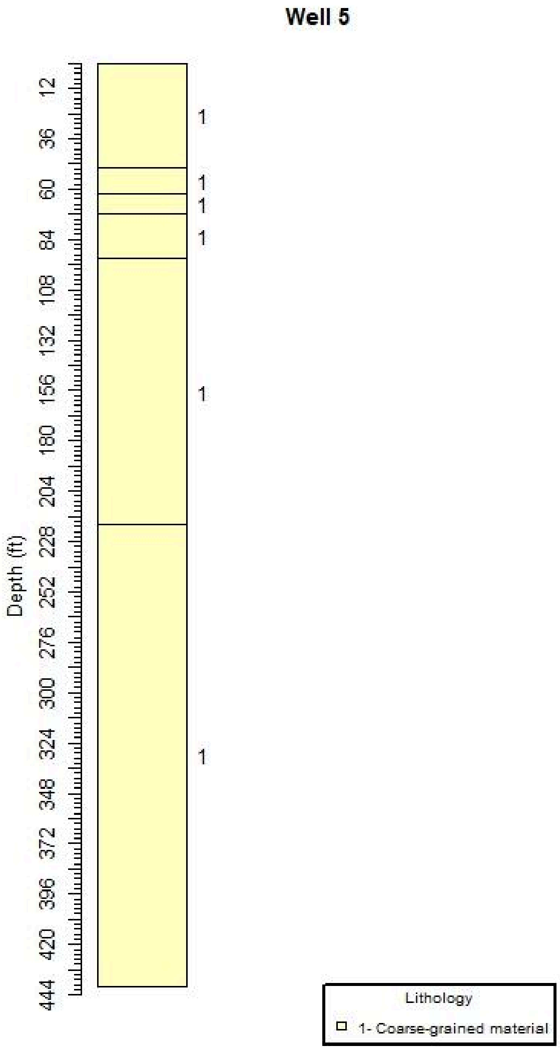


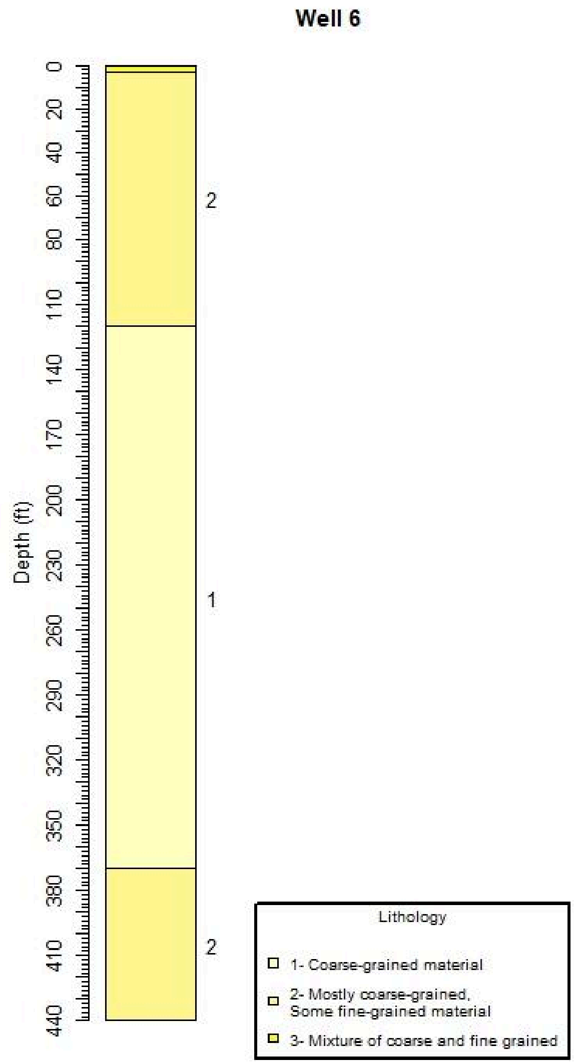
Well 3 (WCR2016-008253) & Well 4 (WCR2001-012698)



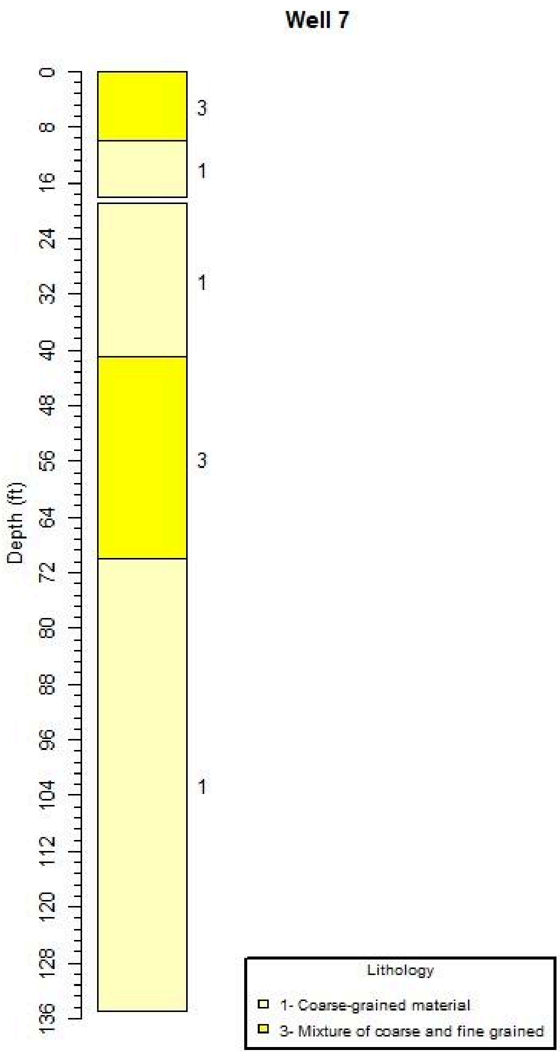


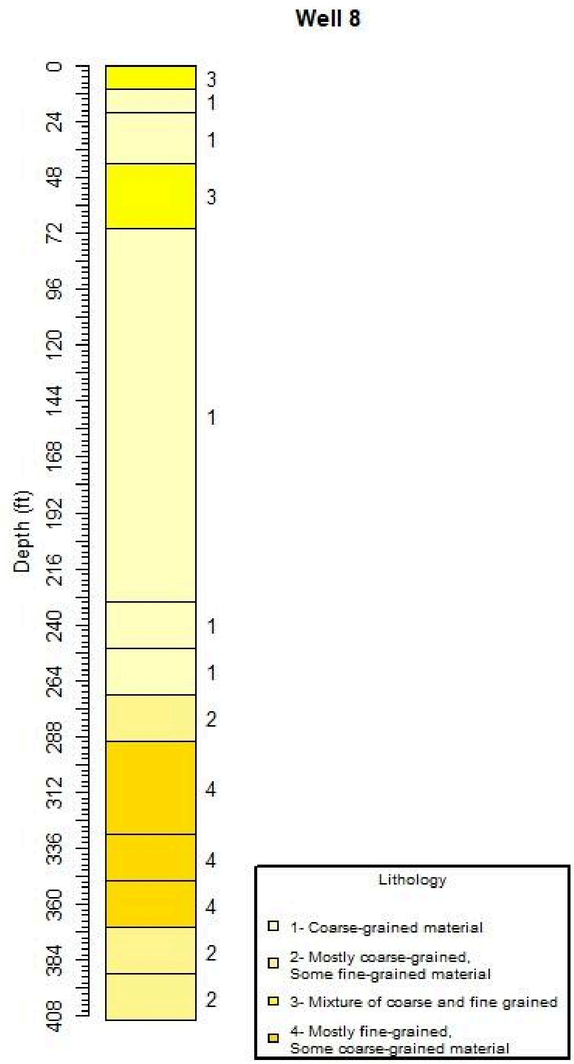
Well 5 (WCR2012-008680) & Well 6 (WCR2008-011034)



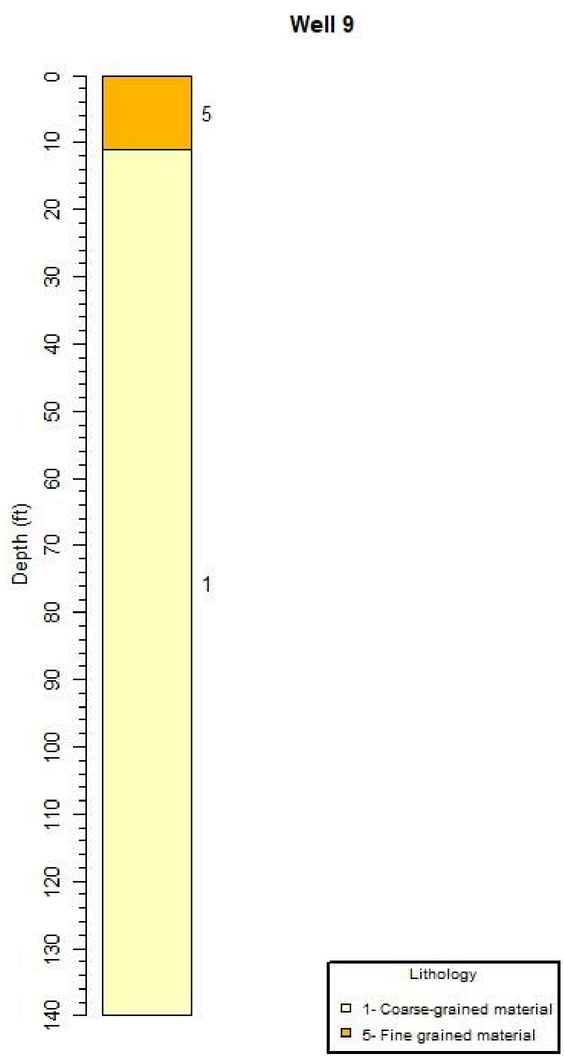


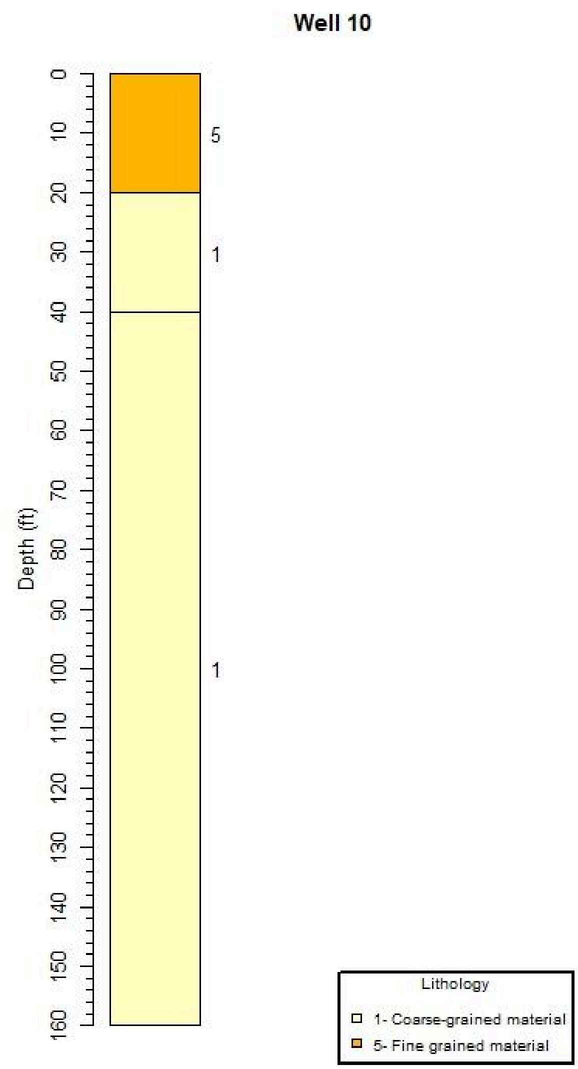
Well 7 (WCR2002-012607) & Well 8 (WCR2018-009168)



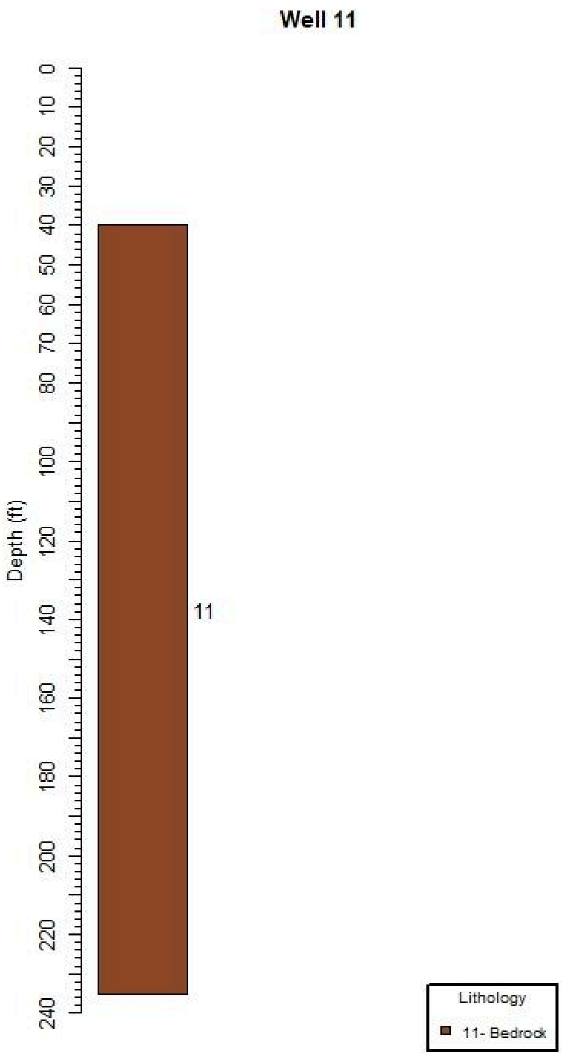


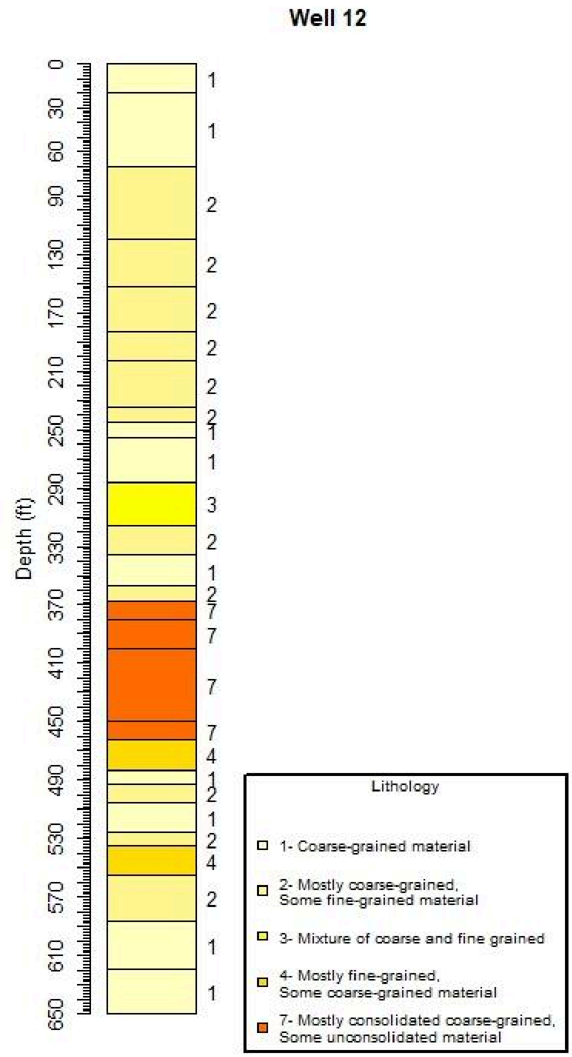
Well 9 (WCR2007-012990) & Well 10 (WCR2007-012895)



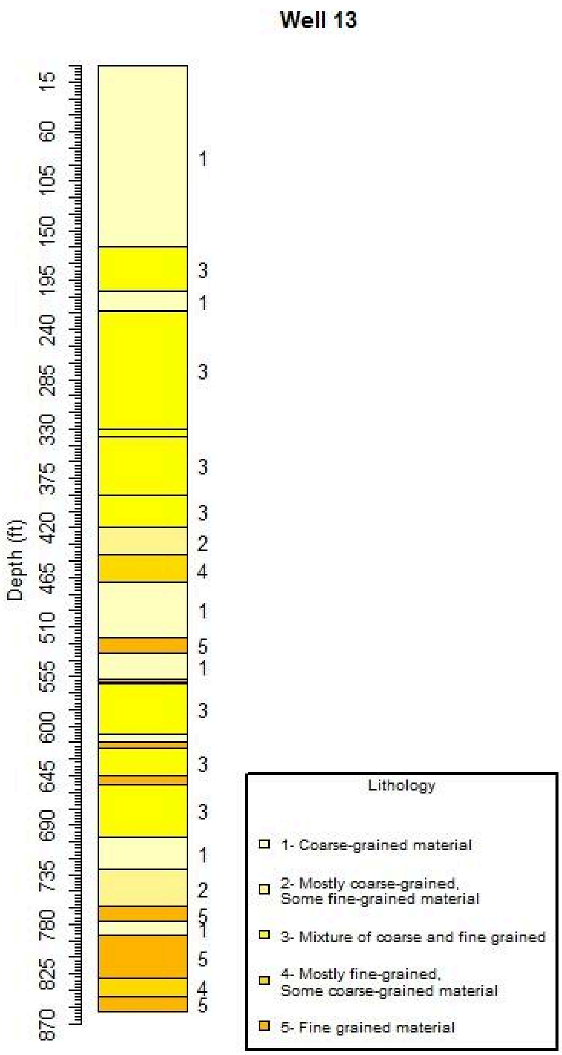


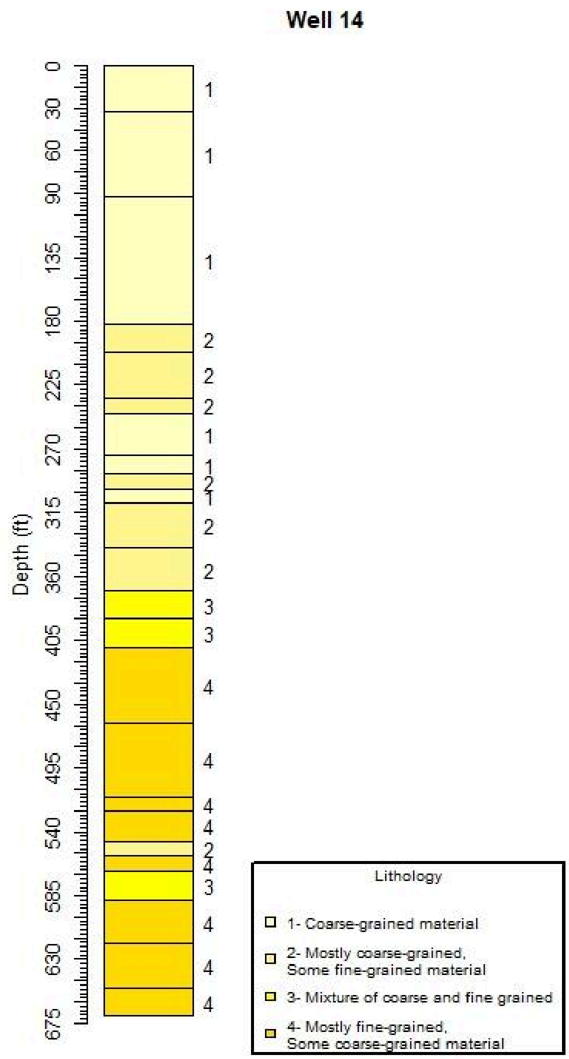
Well 11 (WCR2003-015339) & Well 12 (WCR2010-010156)



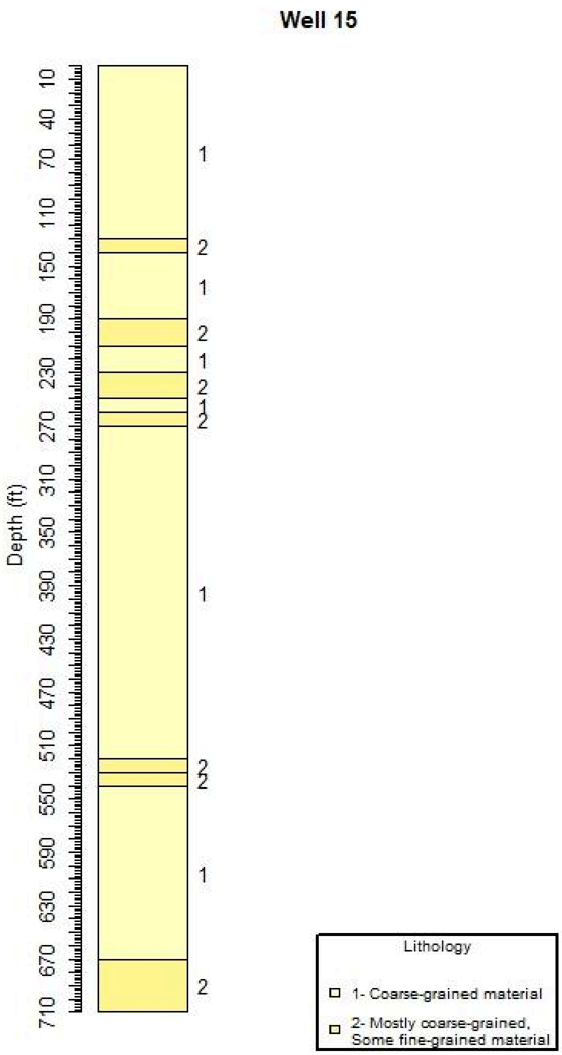


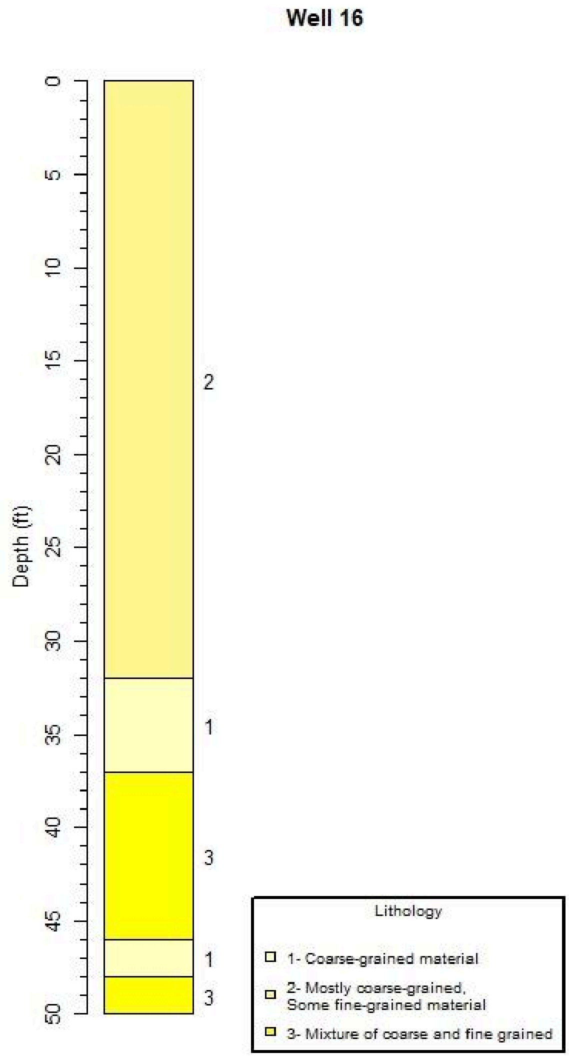
Well 13 (WCR2004-015524) & Well 14 (WCR2010-010413)



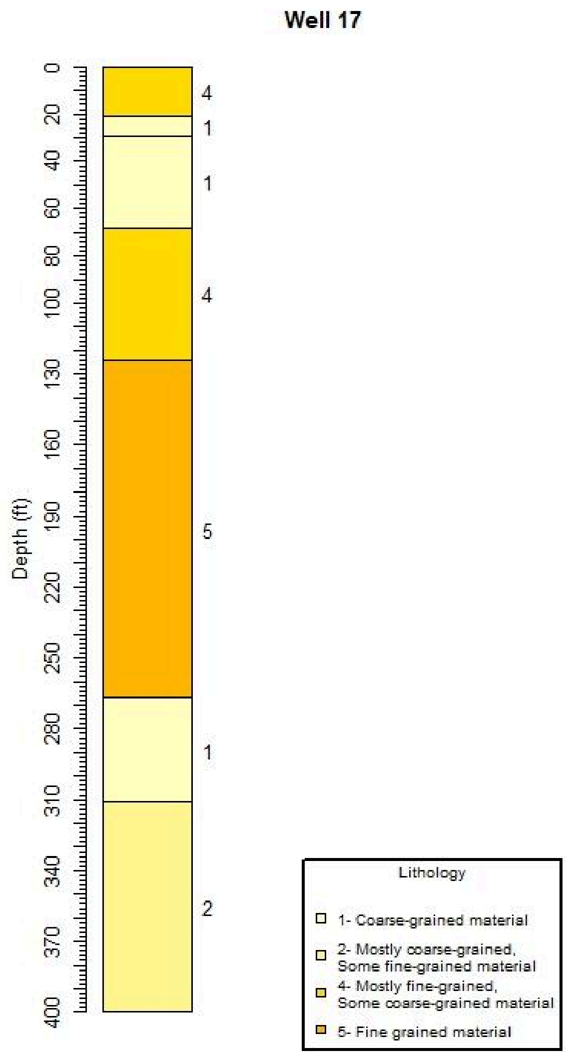


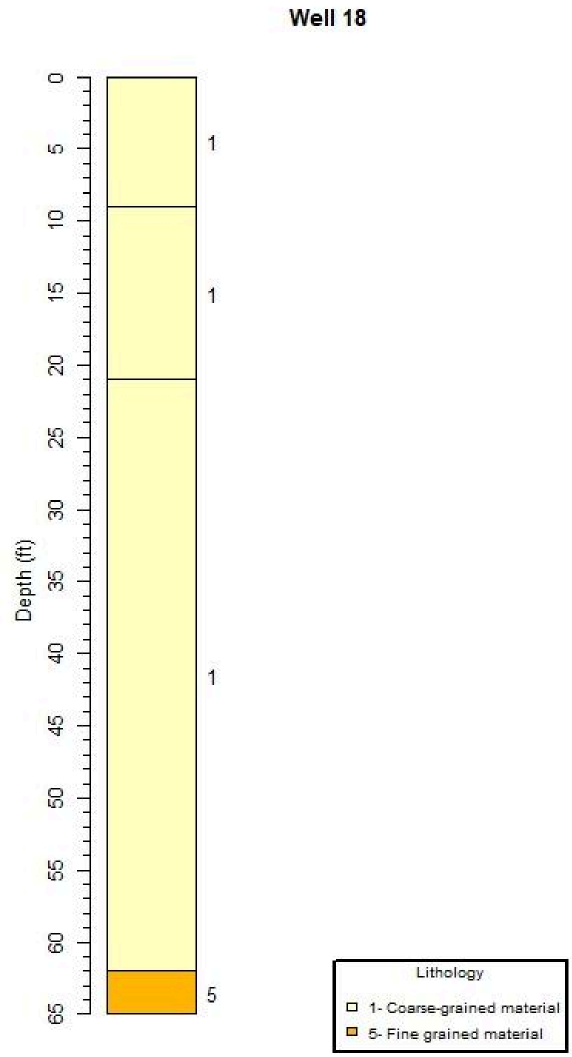
Well 15 (WCR2003-011868) & Well 16 (WCR1987-014407)



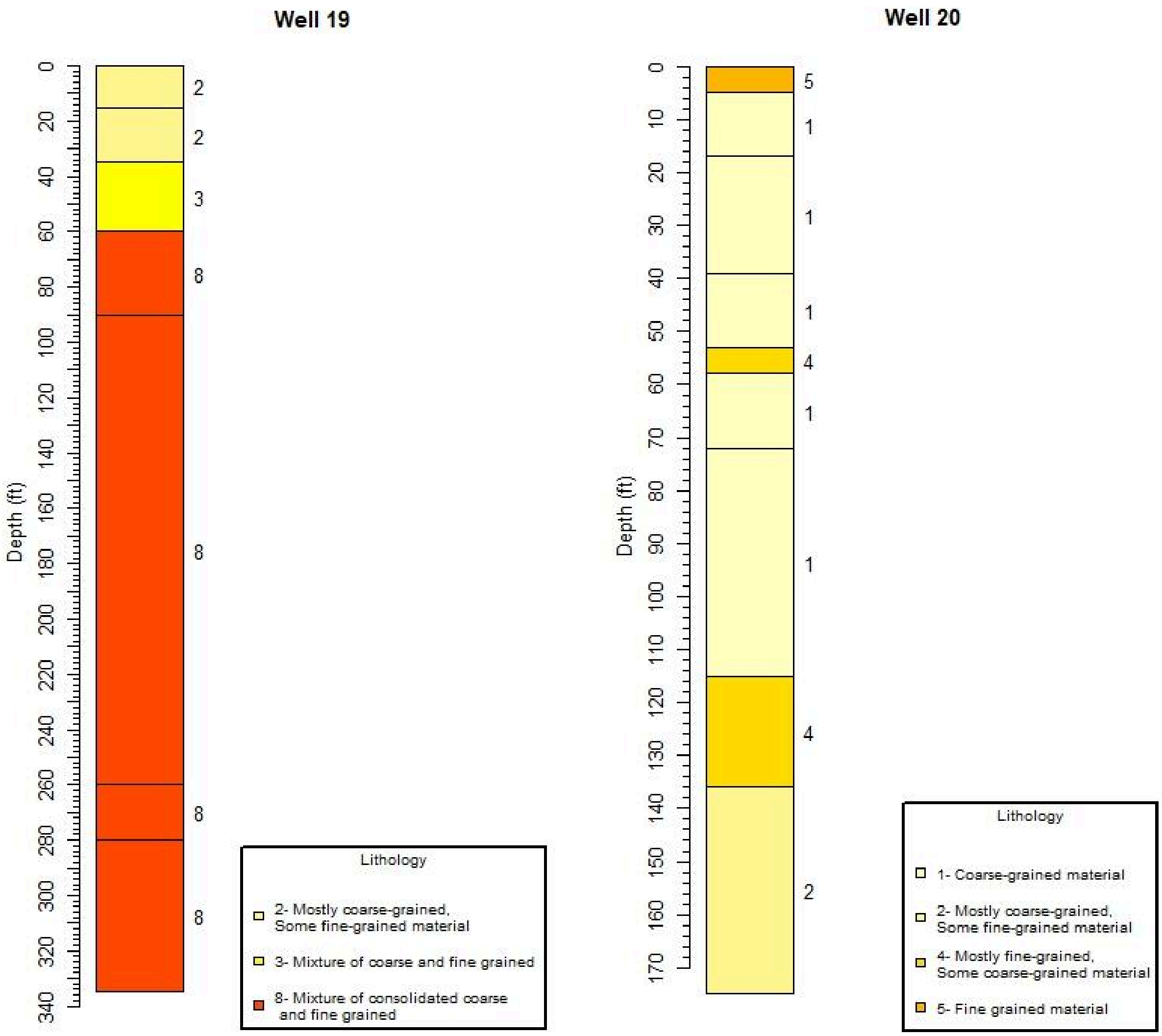


Well 17 (WCR2016-008246) & Well 18 (WCR1992-017541)

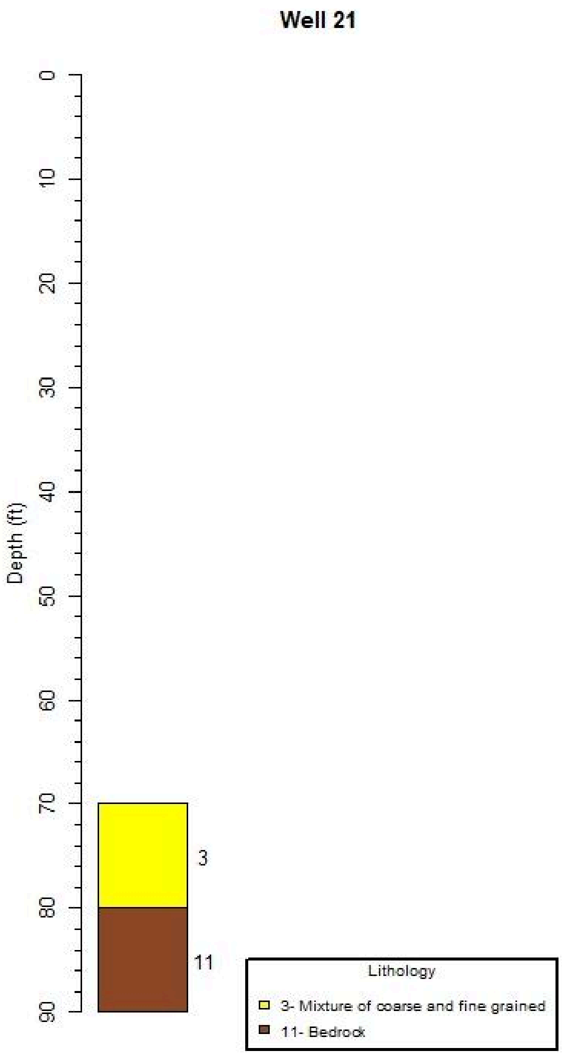


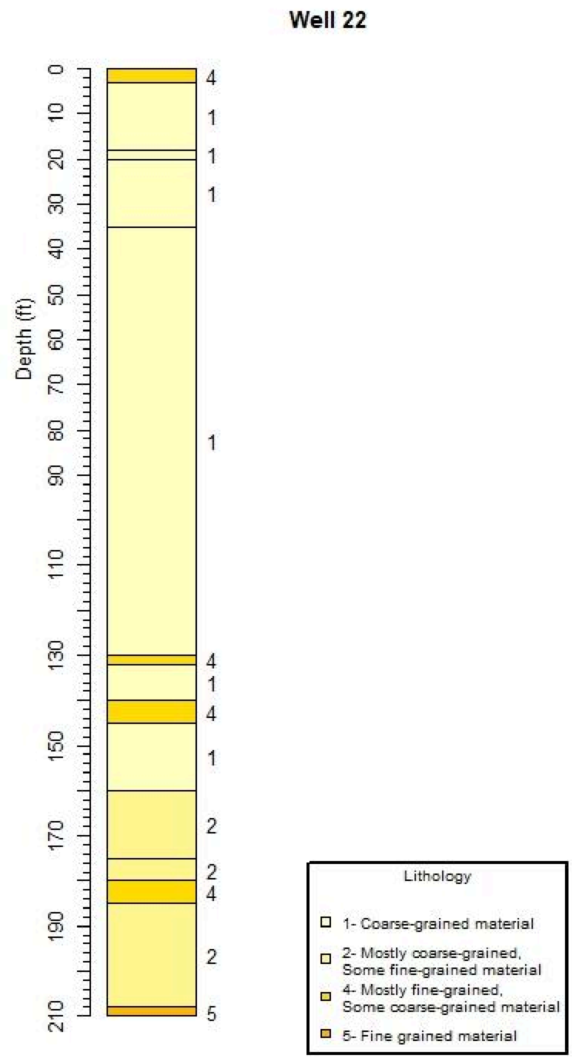


Well 19 (WCR2002-014221) & Well 20 (WCR1975-003220)

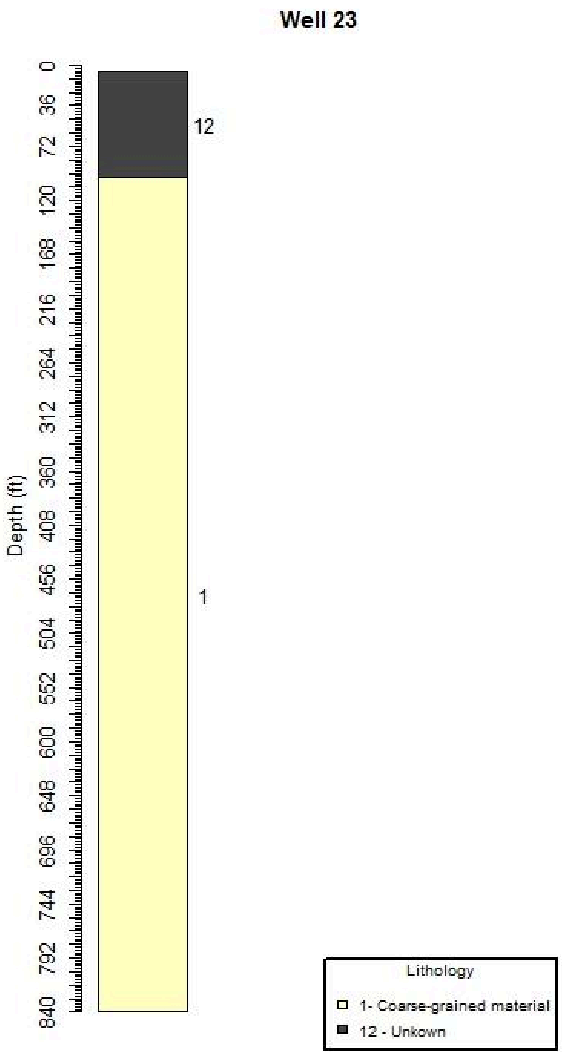


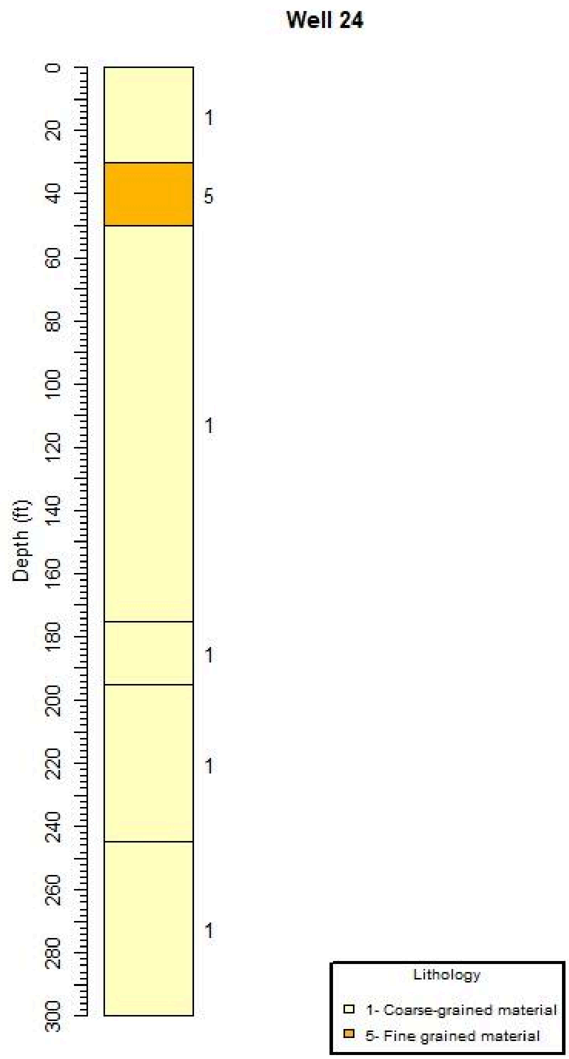
Well 21 (WCR2004-012771) & Well 22 (WCR1998-010940)



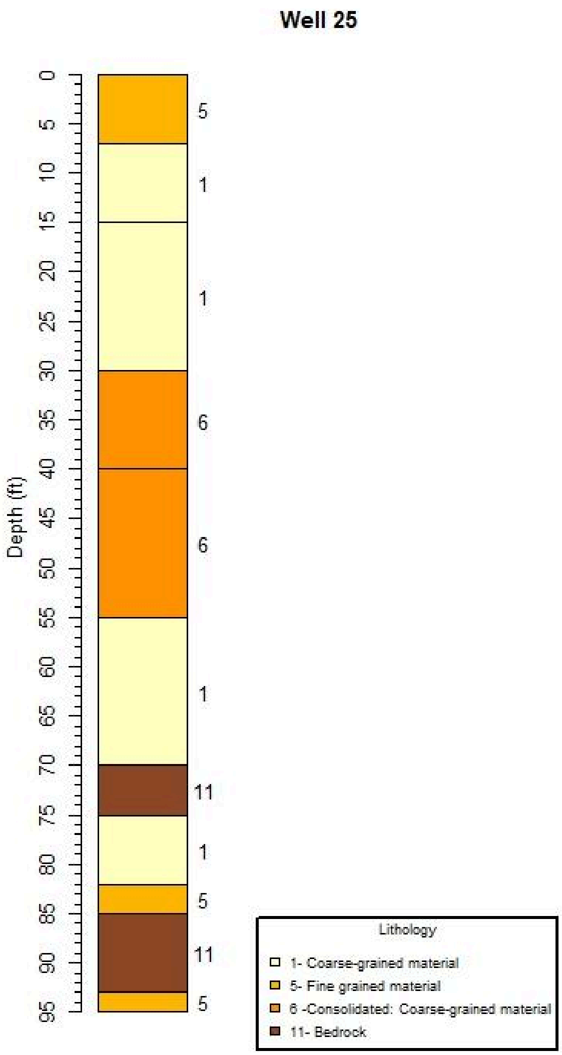


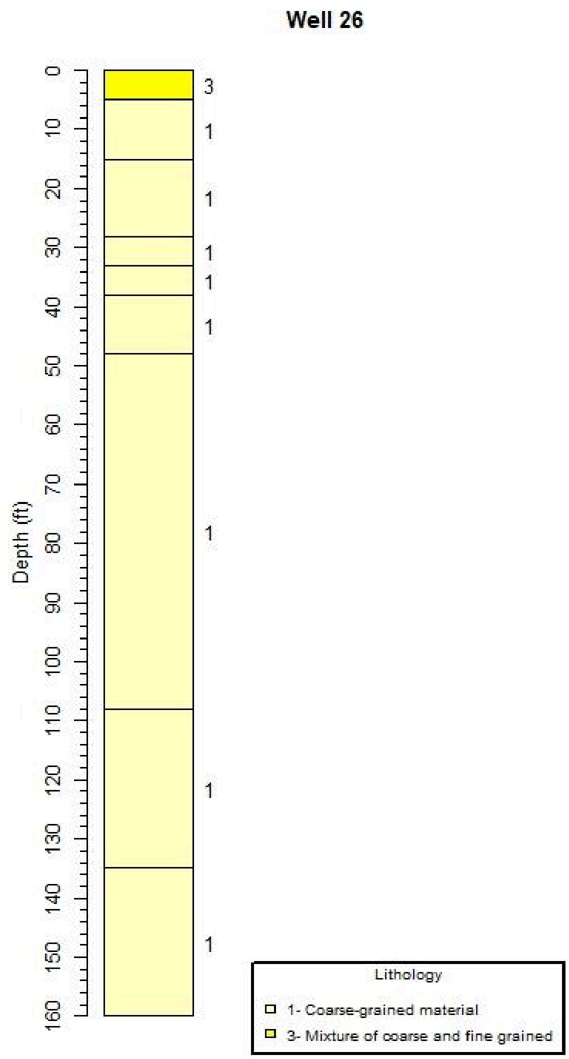
Well 23 (WCR2004-015953) & Well 24 (WCR1998-011367)



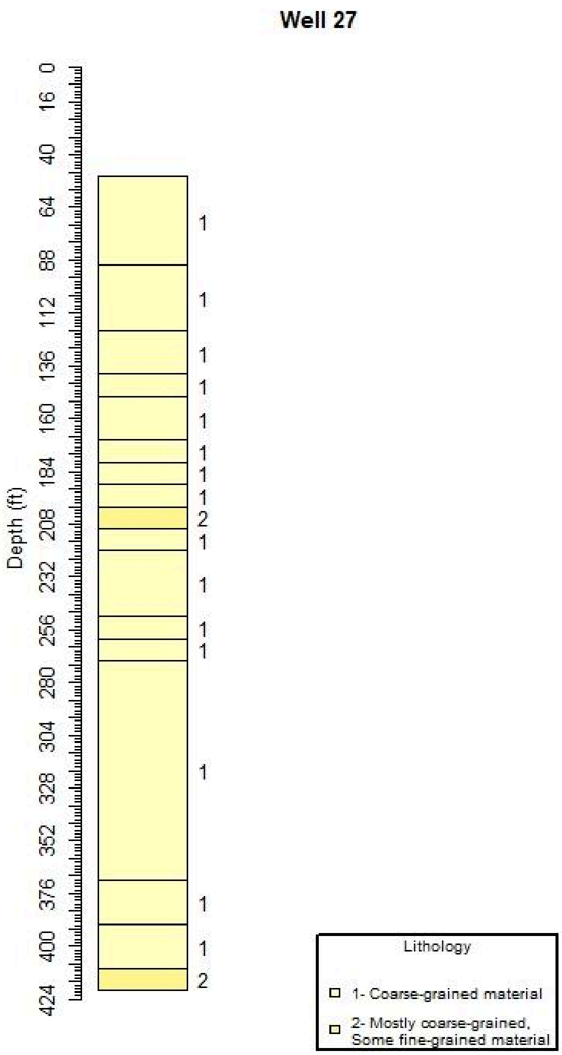


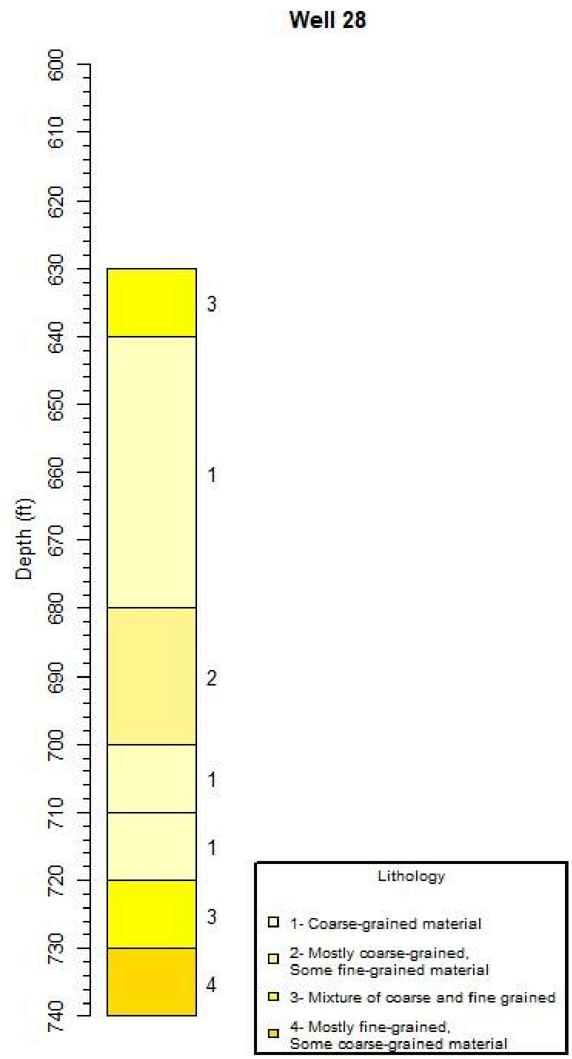
Well 25 (WCR1998-010943) & Well 26 (WCR2016-003545)



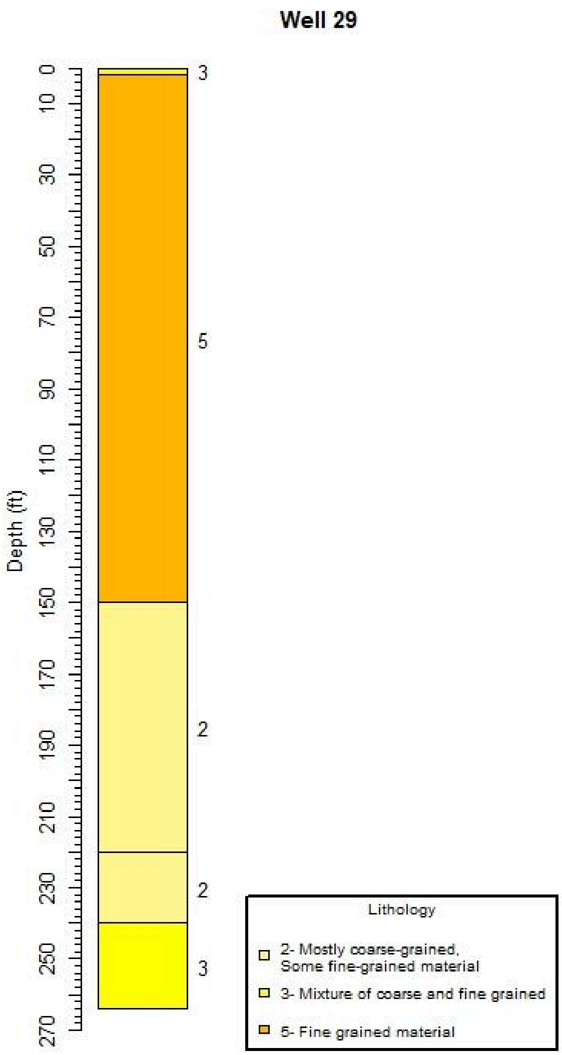


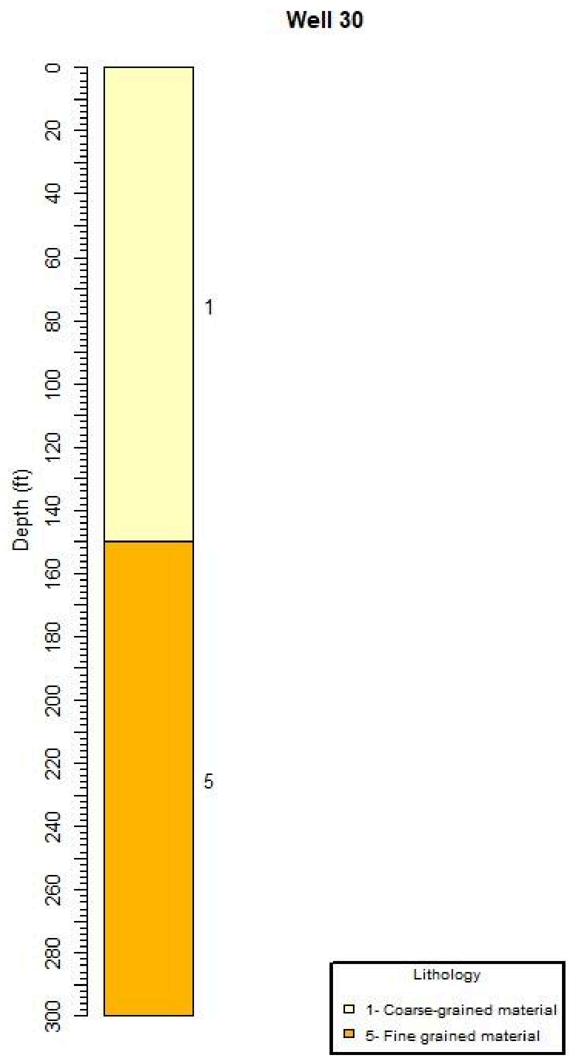
Well 27 (WCR2017-006033) & Well 28 (WCR2010-010863)



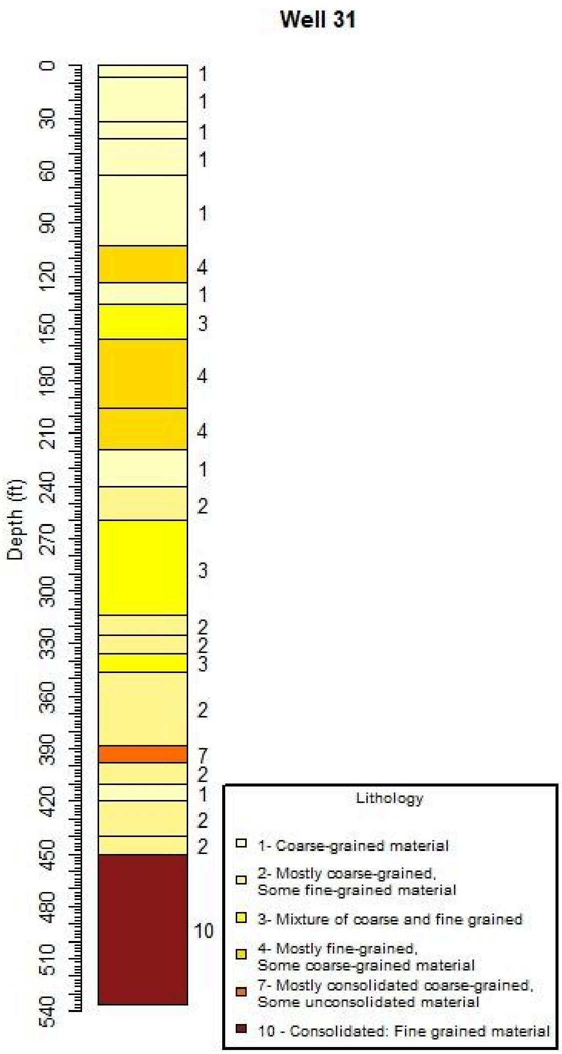


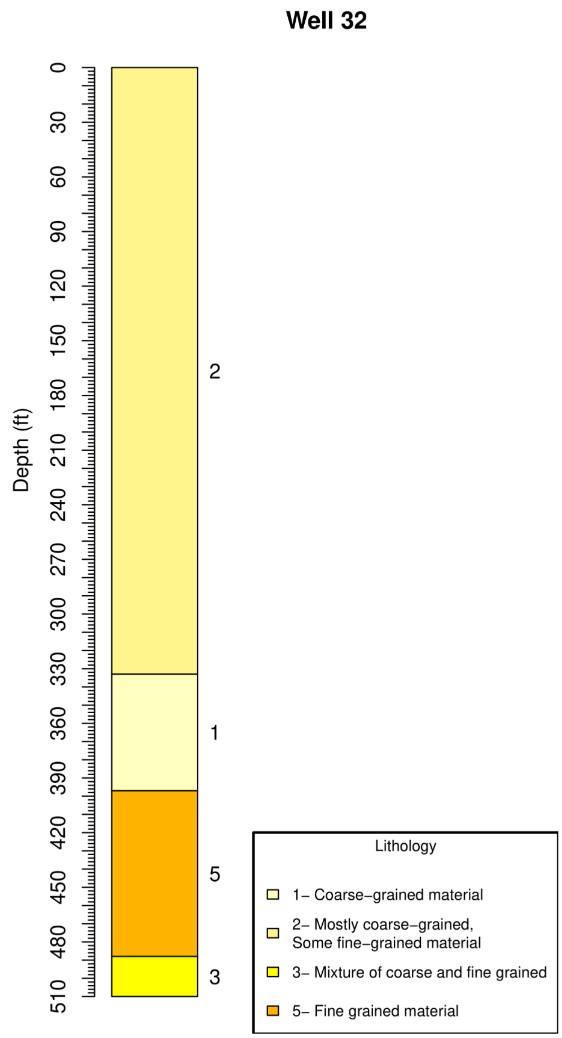
Well 29 (WCR2010-010444) & Well 30 (WCR2014-007922)



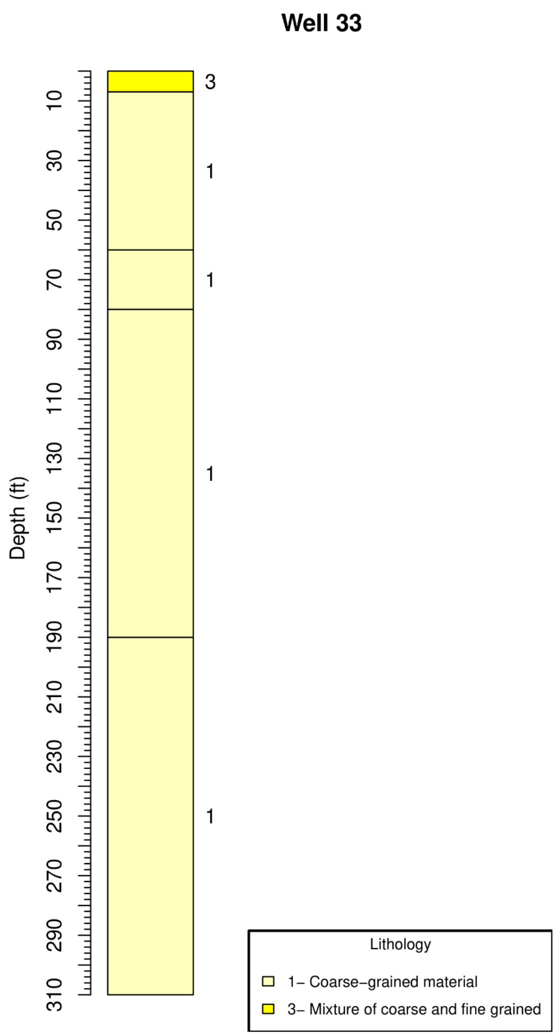


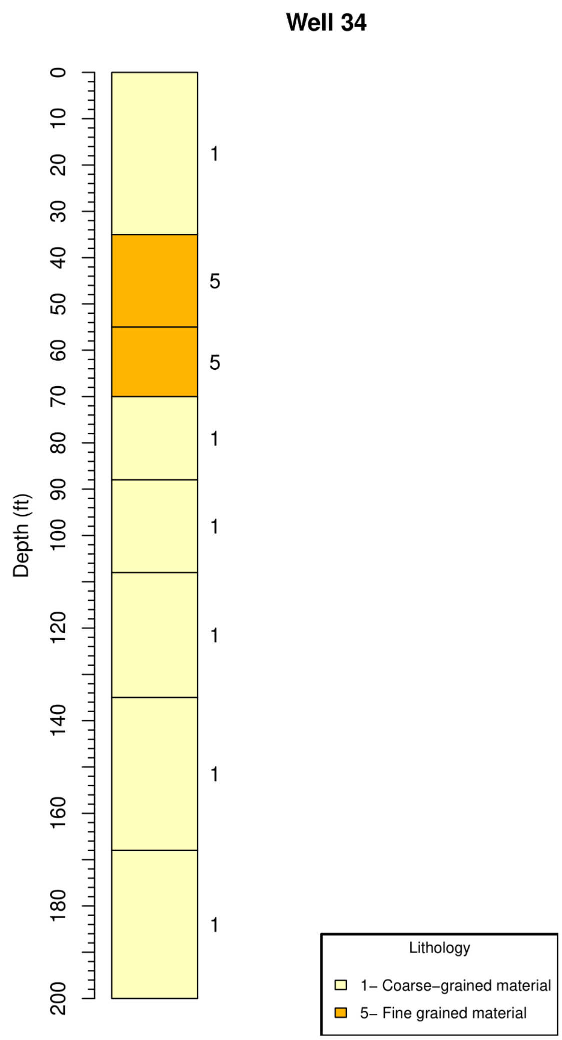
Well 31 (WCR2017-002288) & Well 32 (WCR2018-005473)



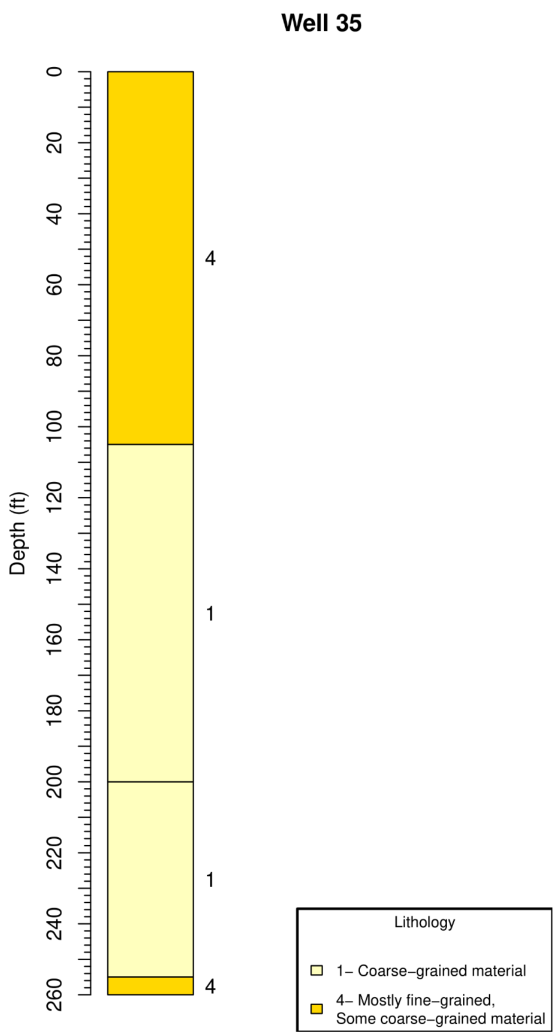


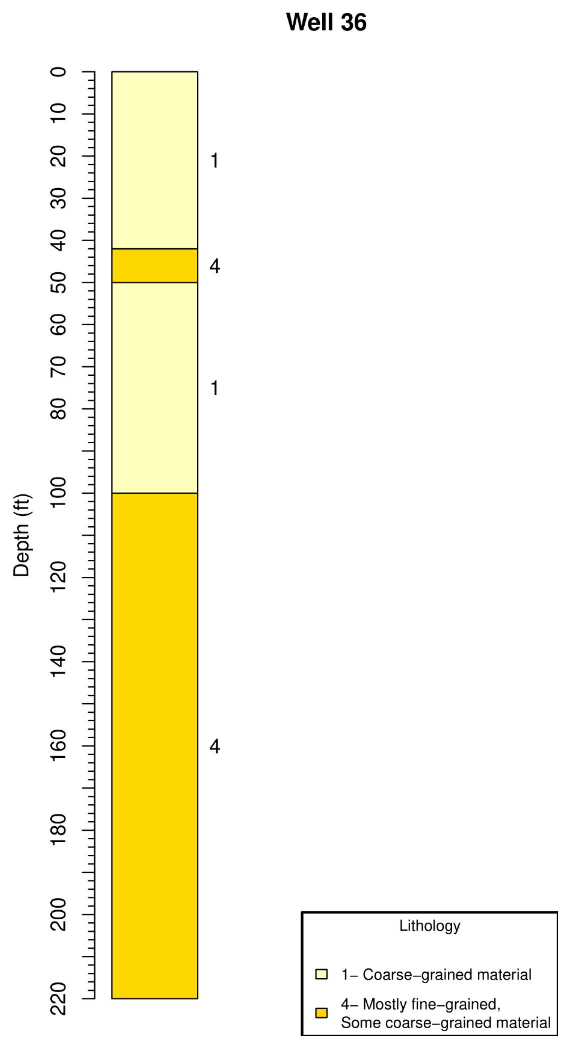
Well 33 (WCR2011-008722) & Well 34 (WCR2017-006208)



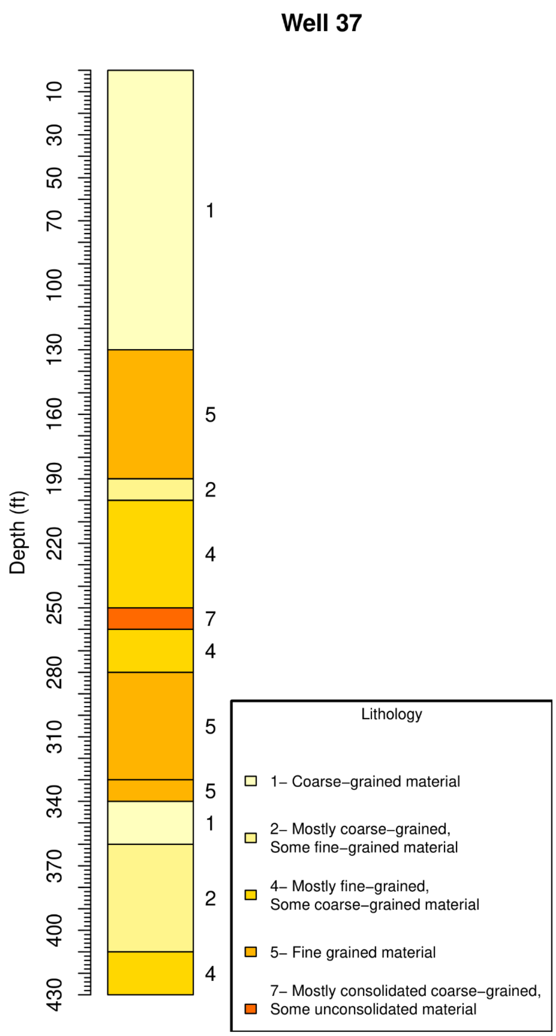


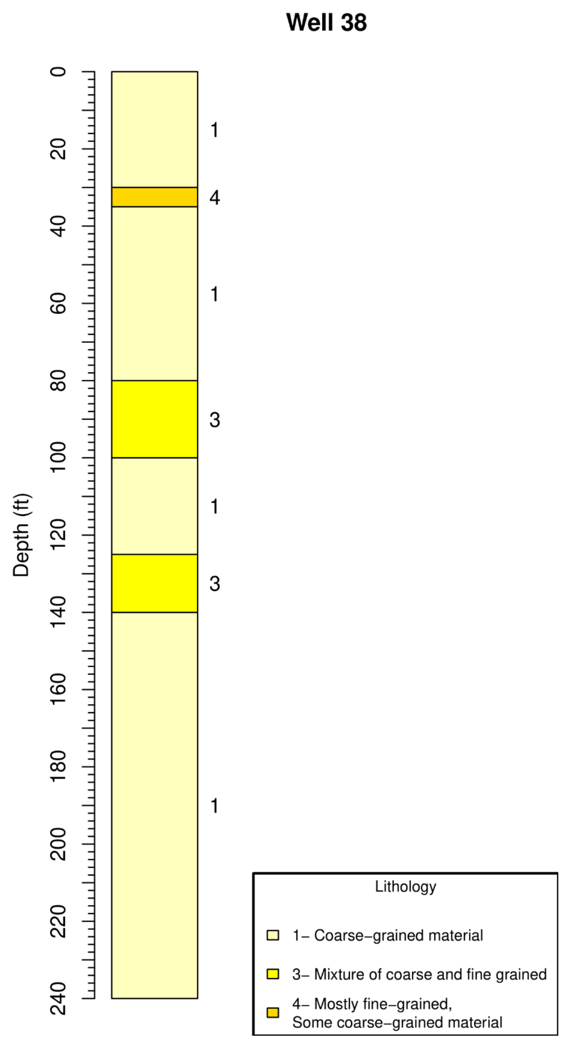
Well 35 (WCR2002-012305) & Well 36 (WCR2005-014510)



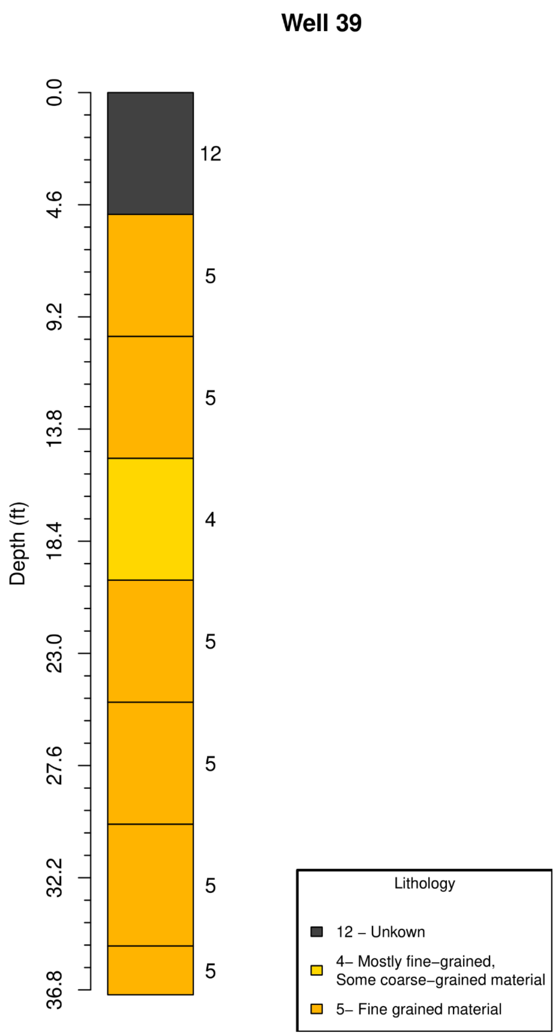


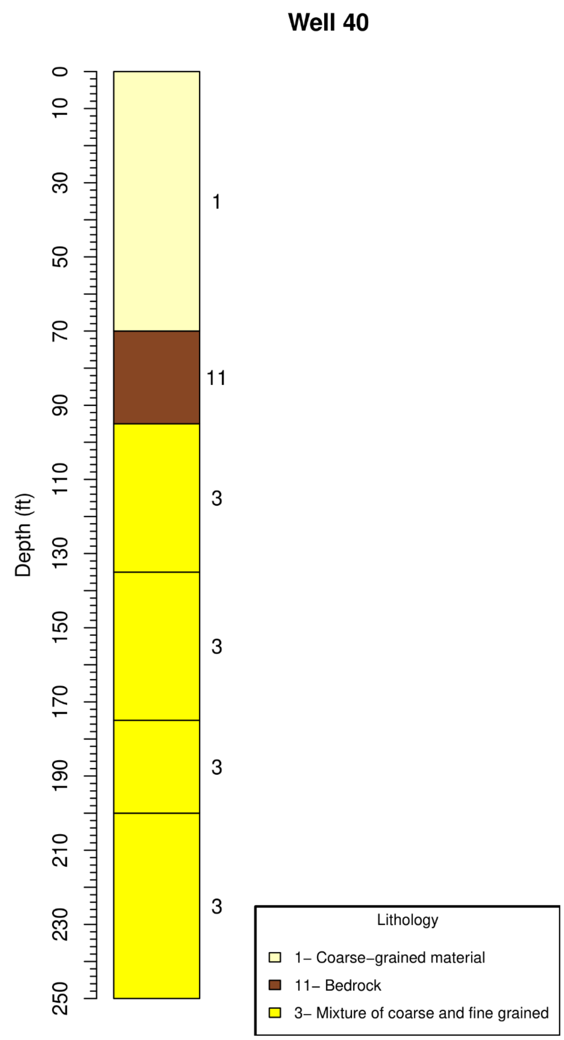
Well 37 (WCR2013-009374) & Well 38 (WCR2017-006096)



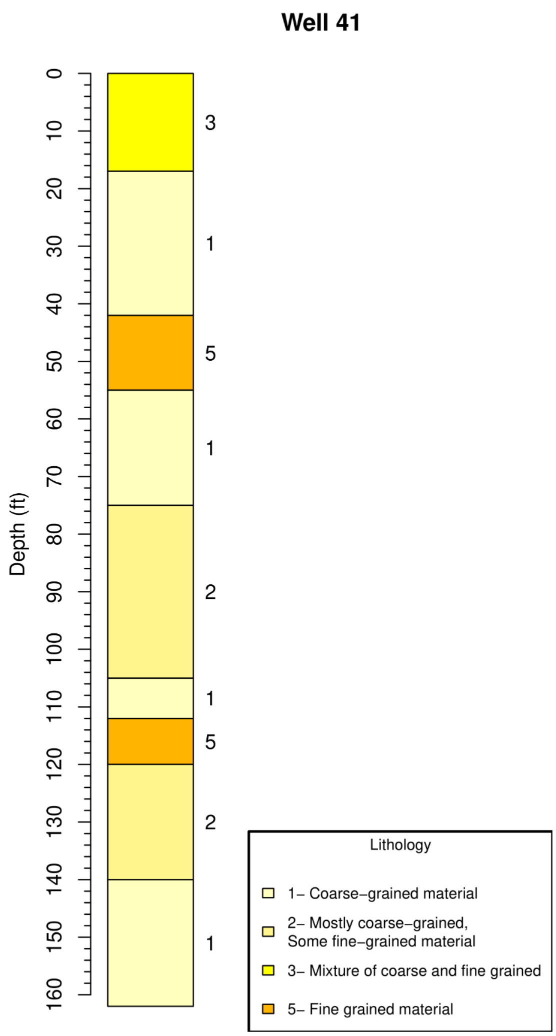


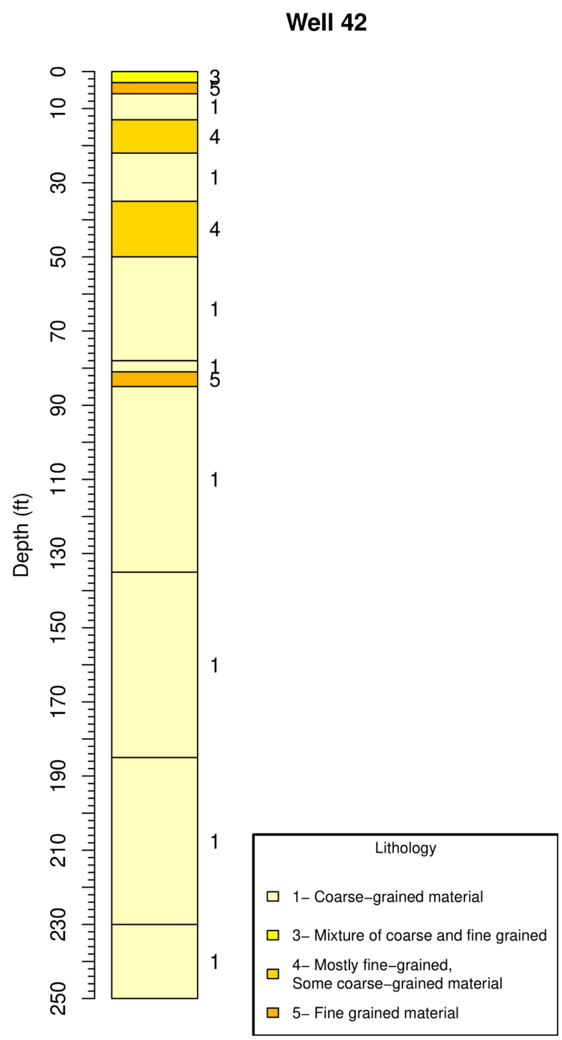
Well 39 (WCR2001-014788) & Well 40 (WCR1974-004128)



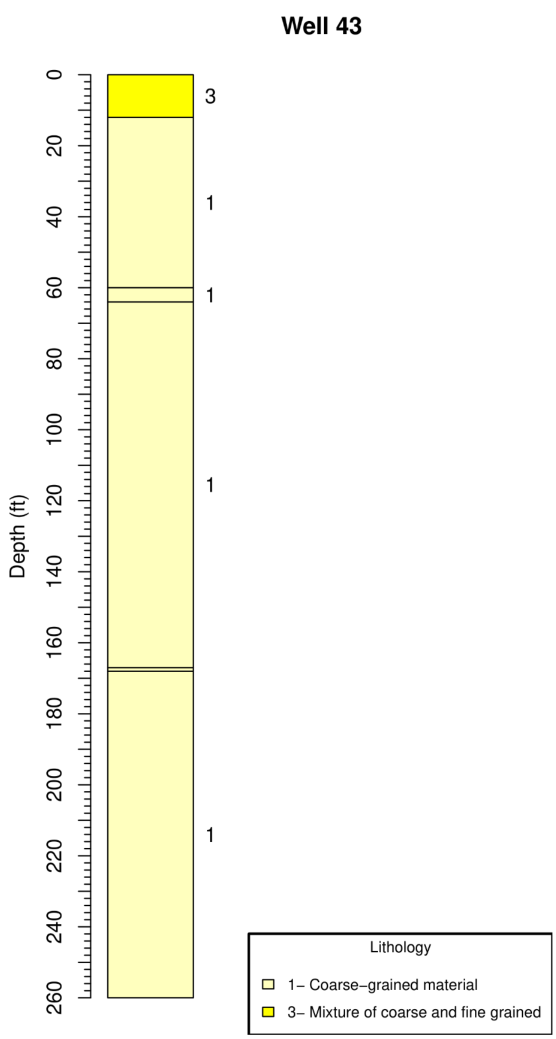


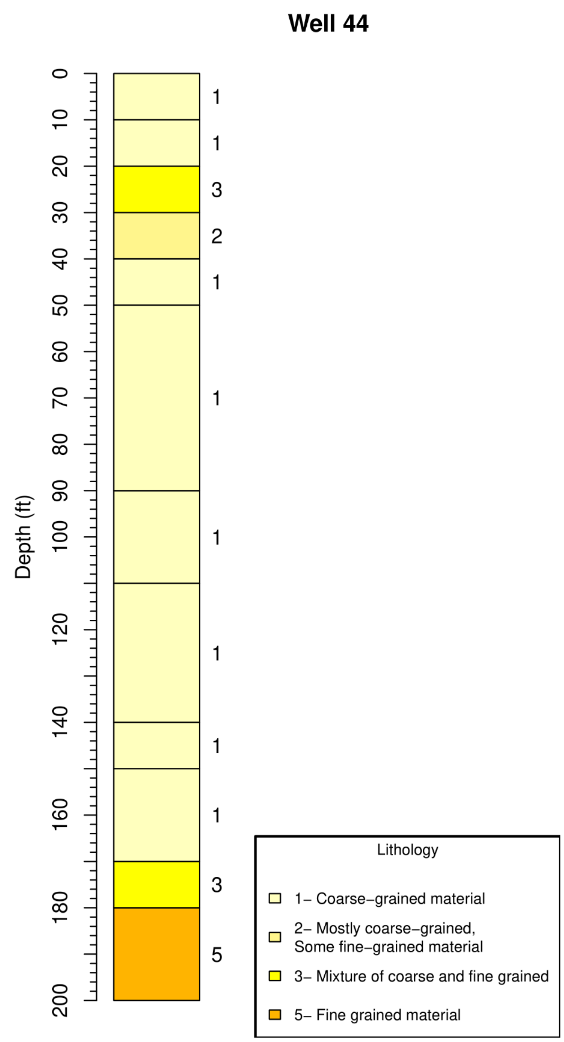
Well 41 (WCR2007-012988) & Well 42 (WCR2006-011431)


Well 41
Depth (ft)
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
3
1
5
1
2
1
5
2
1
Lithology
1– Coarse–grained material
2– Mostly coarse–grained,
Some fine–grained material
3– Mixture of coarse and fine grained
5– Fine grained material

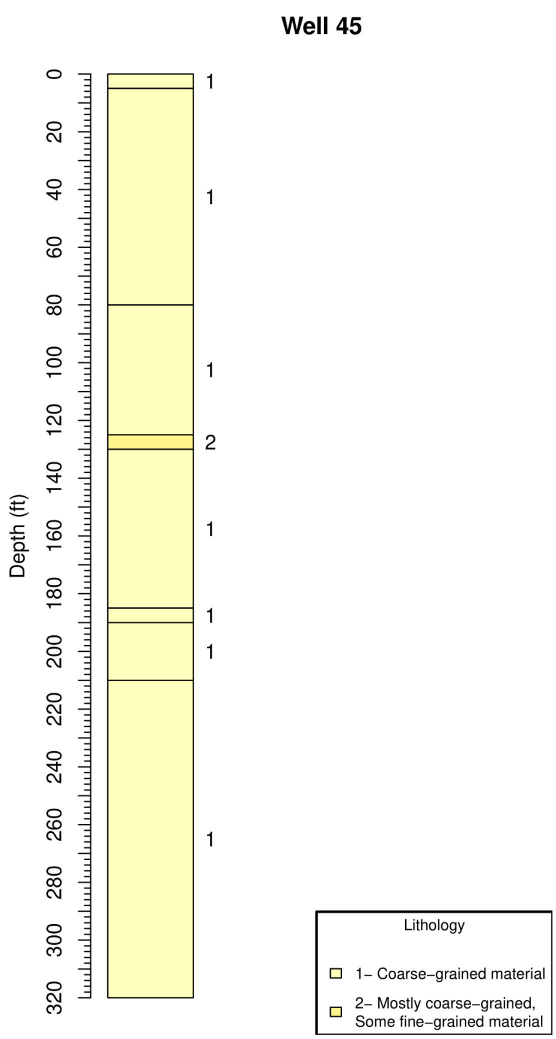

Well 42
Depth (ft)
0
10
30
50
70
90
110
130
150
170
190
210
230
250
3
5
1
4
1
4
1
1
5
1
1
1
1
Lithology
1– Coarse–grained material
3– Mixture of coarse and fine grained
4– Mostly fine–grained,
Some coarse–grained material
5– Fine grained material

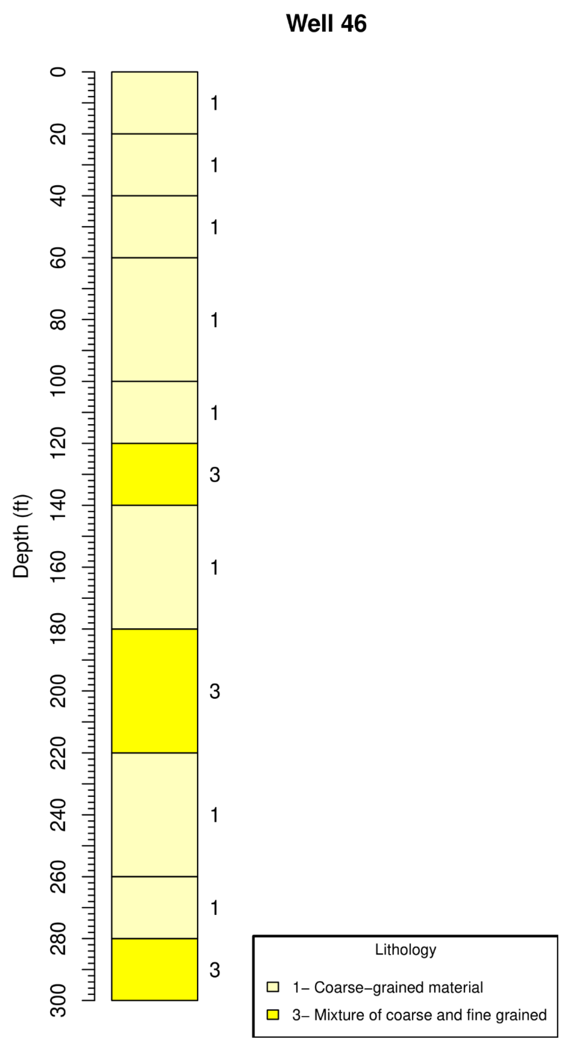
Well 43 (WCR1999-010350) & Well 44 (WCR2016-005853)





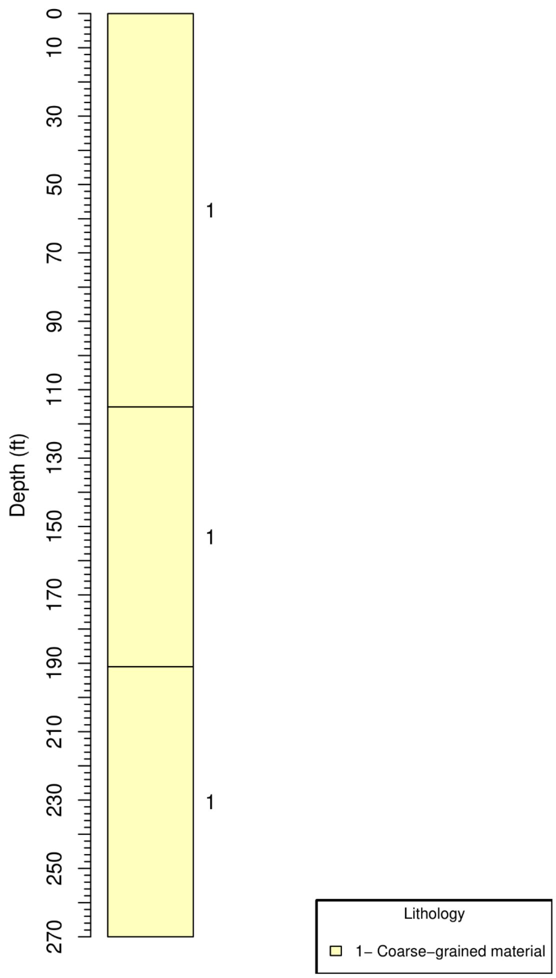
Well 45 (WCR2011-008721) & Well 46 (WCR2005-014414)



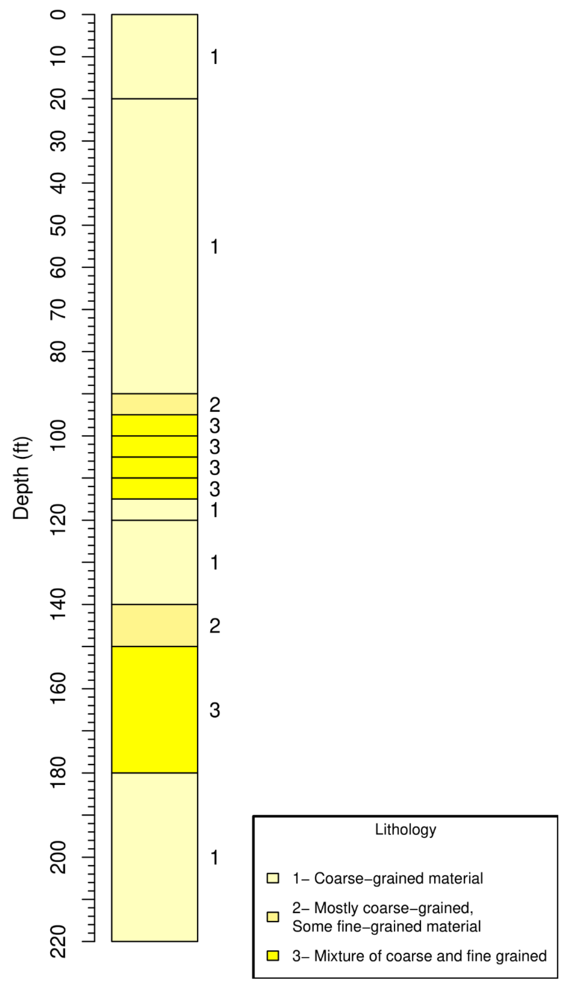


Well 47 (WCR2005-011645) & Well 48 (WCR2005-016688)

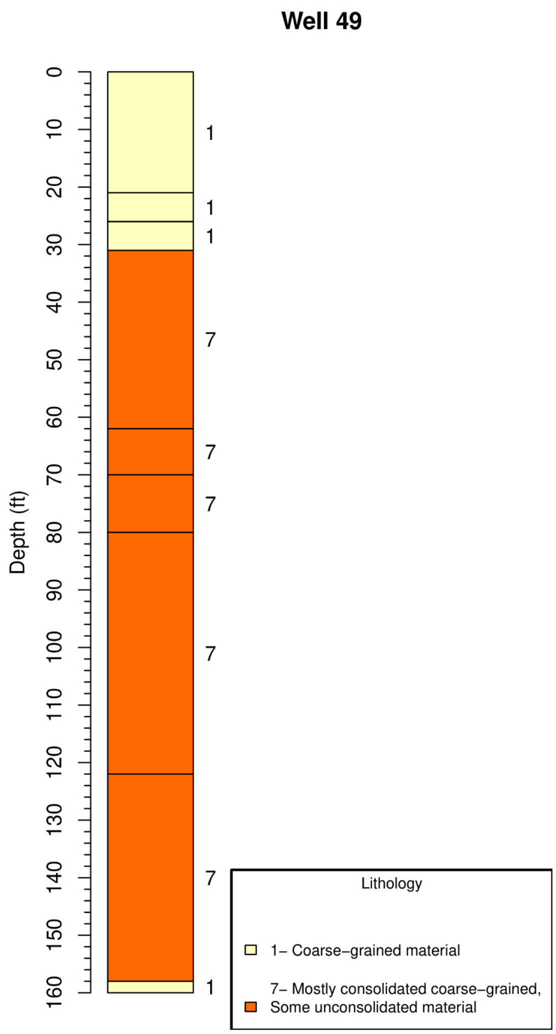
Well 47

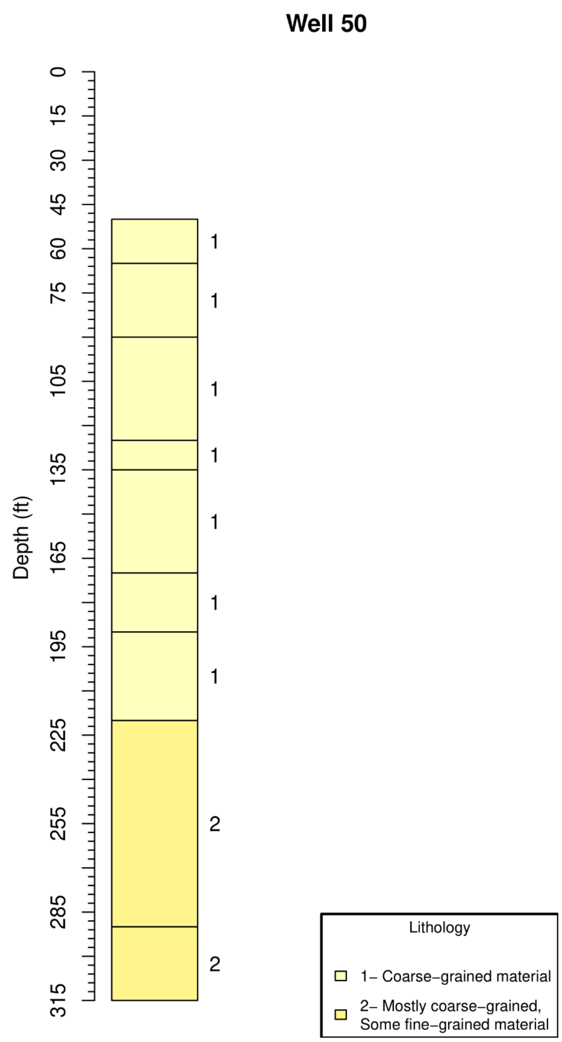


Well 48



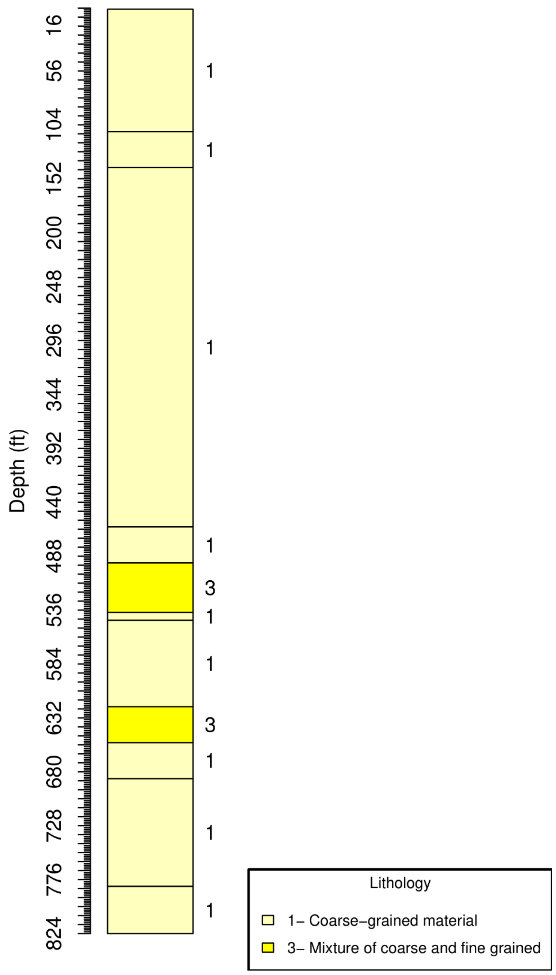
Well 49 (WCR2010-010106) & Well 50 (WCR2010-010159)



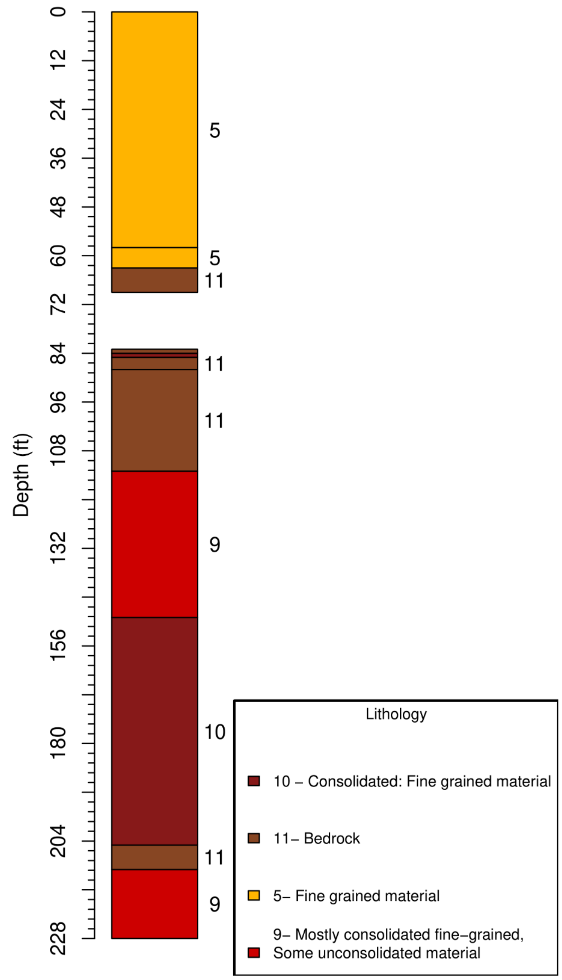


Well 51 (WCR2014-008854) & Well 52 (WCR1988-016945)

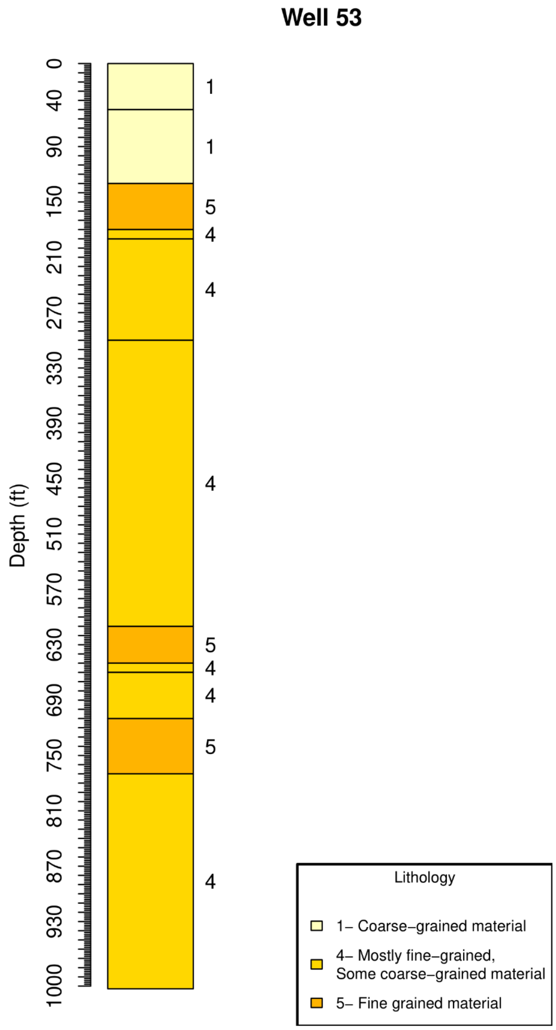
Well 51

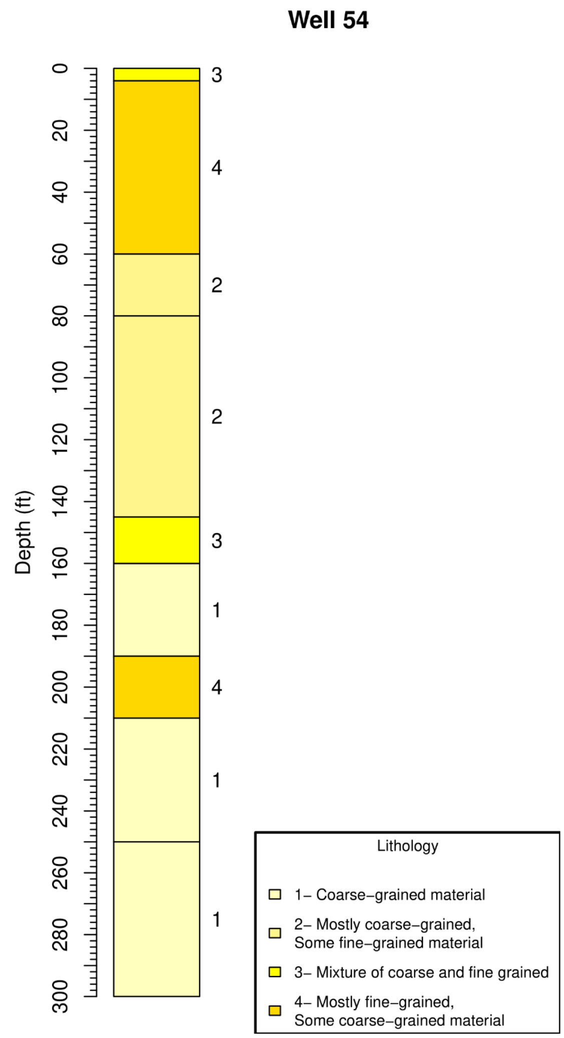


Well 52

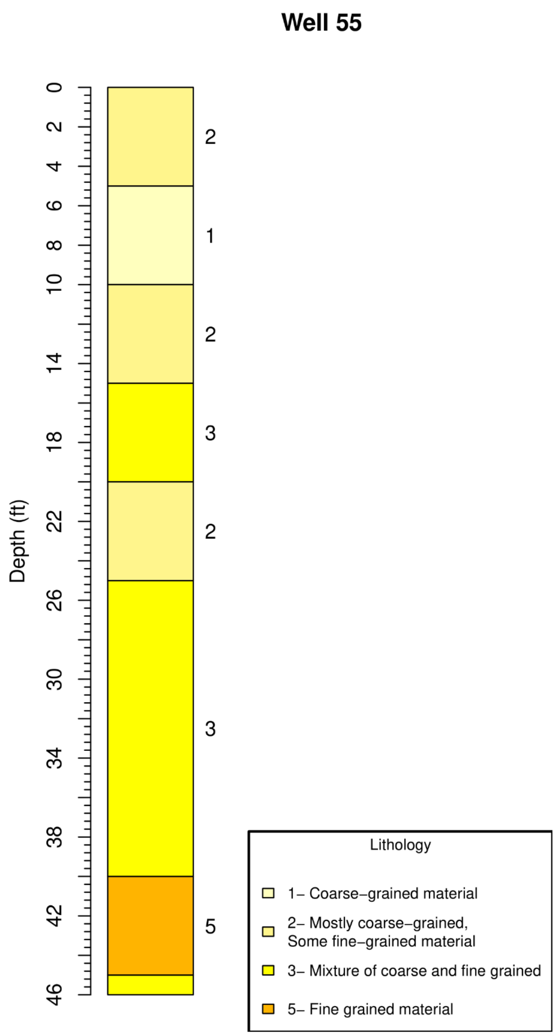


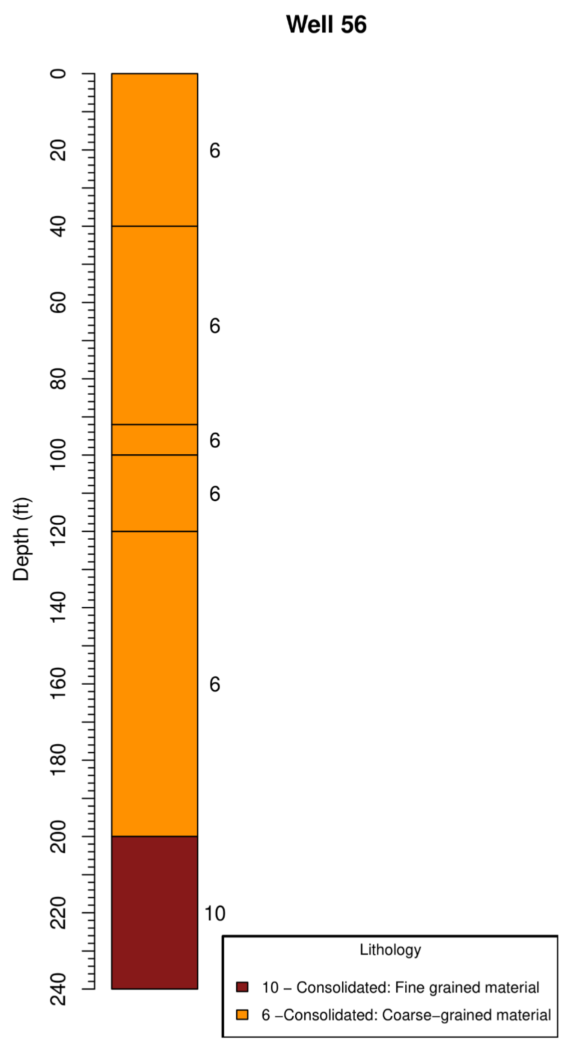
Well 53 (WCR2013-009055) & Well 54 (WCR2006-013424)



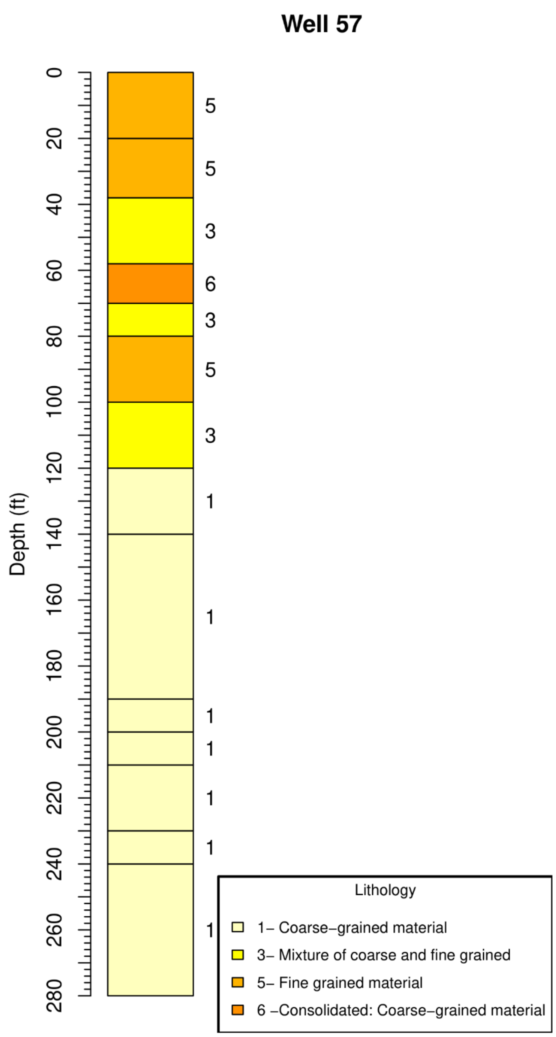


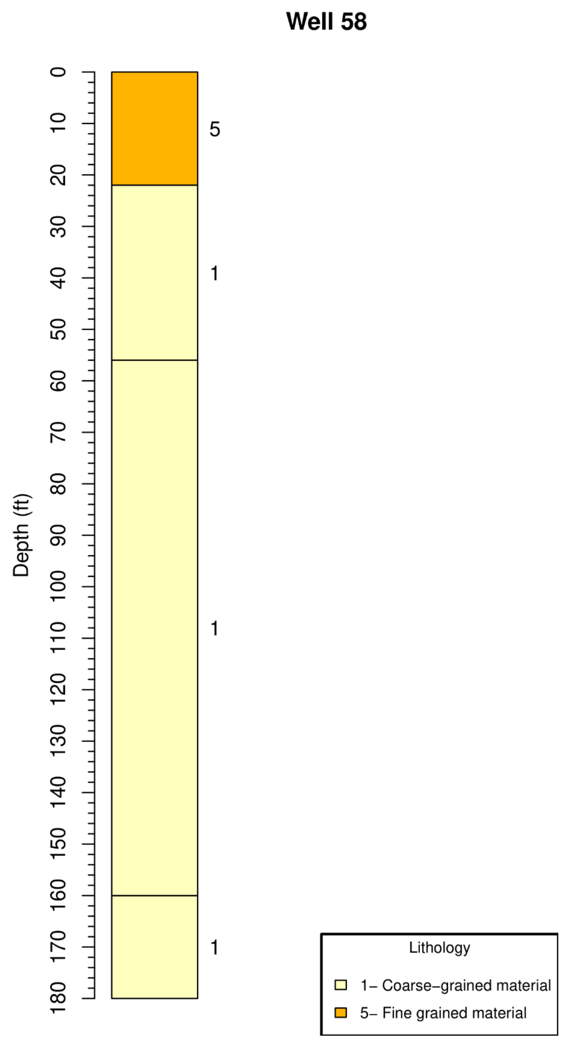
Well 55 (WCR2011-009259) & Well 56 (WCR2005-016695)



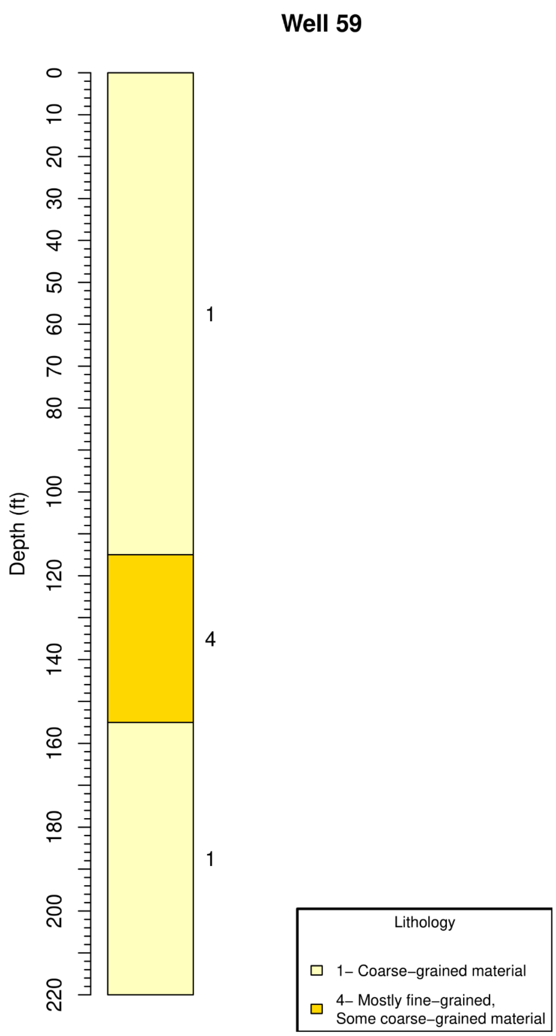


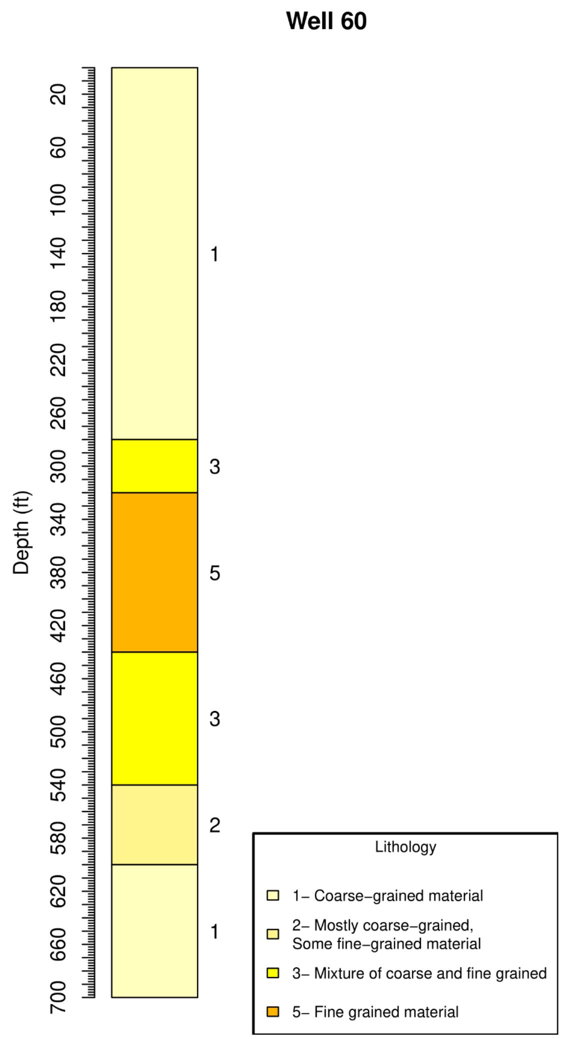
Well 57 (WCR0307632) & Well 58 (WCR2008-010999)



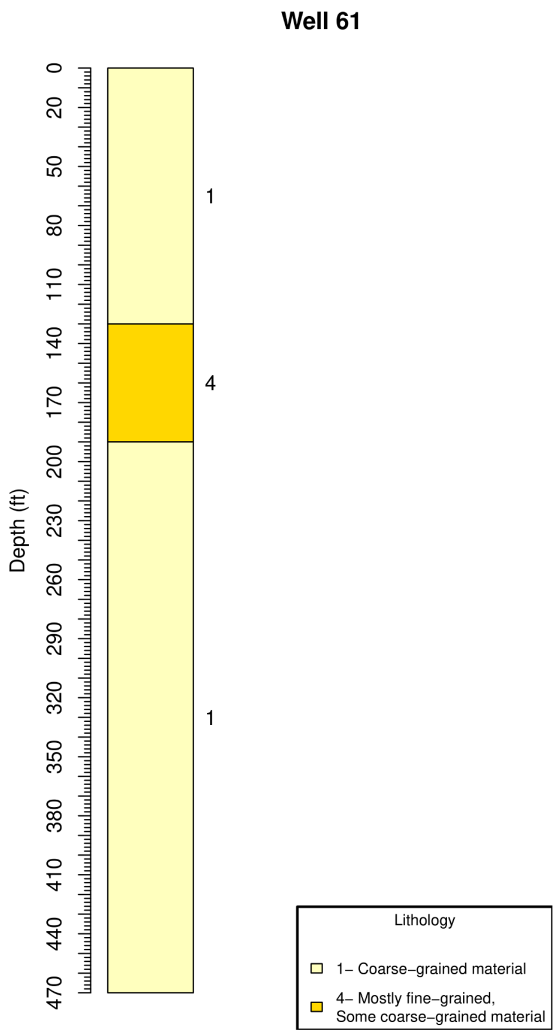


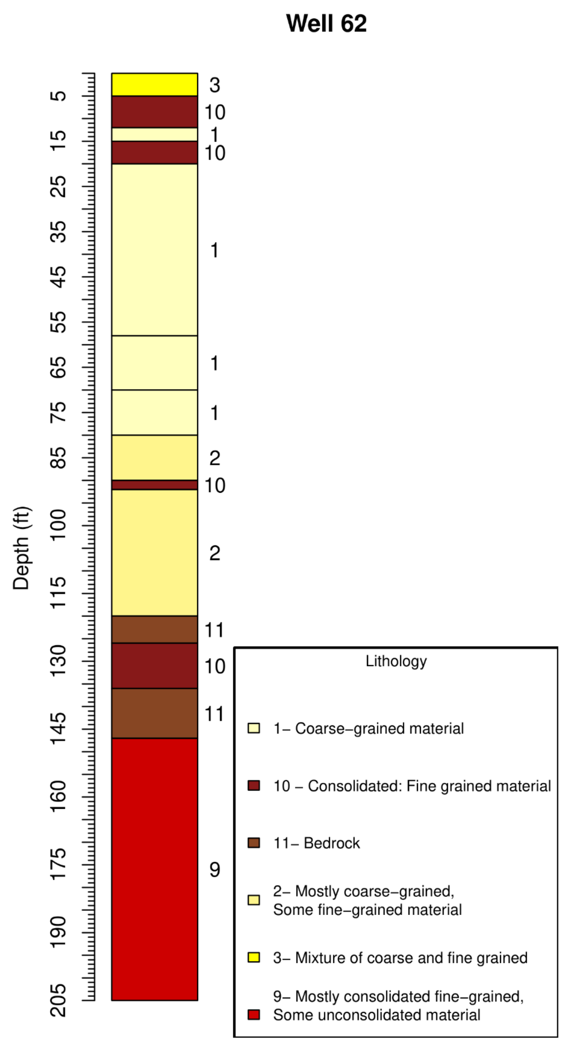
Well 59 (WCR2007-012991) & Well 60 (WCR2013-011287)


Well 59
Depth (ft)
0
10
20
30
40
50
60
70
80
100
120
140
160
180
200
220
1
4
1
Lithology
1− Coarse−grained material
4− Mostly fine−grained,
Some coarse−grained material

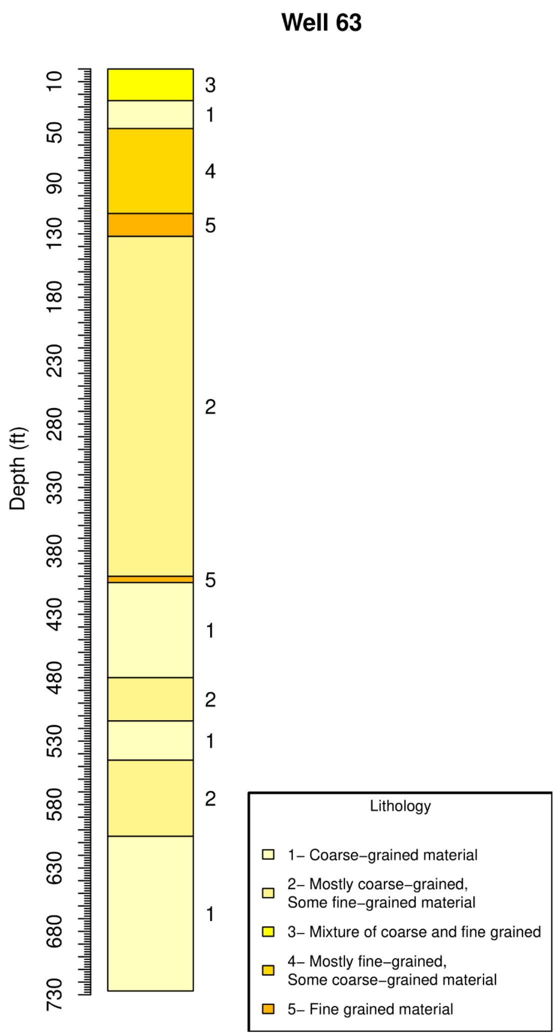

Well 60
Depth (ft)
20
60
100
140
180
220
260
300
340
380
420
460
500
540
580
620
660
700
1
3
5
3
2
1
Lithology
1− Coarse−grained material
2− Mostly coarse−grained,
Some fine−grained material
3− Mixture of coarse and fine grained
5− Fine grained material

Well 61 (WCR1995-012328) & Well 62 (WCR1998-010945)





Well 63 (WCR2001-015603)



3.1.2. Table of Well Id and Well Completion Number

Well Number	Well Completion Number	Well Number	Well Completion Number
Well 1	WCR2004-015336	Well 33	WCR2011-008722
Well 2	WCR2001-015789	Well 34	WCR2017-006208
Well 3	WCR2016-008253	Well 35	WCR2002-012305
Well 4	WCR2001-012698	Well 36	WCR2005-014510
Well 5	WCR2012-008680	Well 37	WCR2013-009374
Well 6	WCR2008-011034	Well 38	WCR2017-006096
Well 7	WCR2002-012607	Well 39	WCR2001-014788
Well 8	WCR2018-009168	Well 40	WCR1974-004128
Well 9	WCR2007-012990	Well 41	WCR2007-012988
Well 10	WCR2007-012895	Well 42	WCR2006-011431
Well 11	WCR2003-015339	Well 43	WCR1999-010350
Well 12	WCR2010-010156	Well 44	WCR2016-005853
Well 13	WCR2004-015524	Well 45	WCR2011-008721
Well 14	WCR2010-010413	Well 46	WCR2005-014414
Well 15	WCR2003-011868	Well 47	WCR2005-011645
Well 16	WCR1987-014407	Well 48	WCR2005-016688
Well 17	WCR2016-008246	Well 49	WCR2010-010106
Well 18	WCR1992-017541	Well 50	WCR2010-010159
Well 19	WCR2002-014221	Well 51	WCR2014-008854
Well 20	WCR1975-003220	Well 52	WCR1988-016945
Well 21	WCR2004-012771	Well 53	WCR2013-009055
Well 22	WCR1998-010940	Well 54	WCR2006-013424
Well 23	WCR2004-015953	Well 55	WCR2011-009259
Well 24	WCR1998-011367	Well 56	WCR2005-016695
Well 25	WCR1998-010943	Well 57	WCR0307632
Well 26	WCR2016-003545	Well 58	WCR2008-010999
Well 27	WCR2017-006033	Well 59	WCR2007-012991
Well 28	WCR2010-010863	Well 60	WCR2013-011287
Well 29	WCR2010-010444	Well 61	WCR1995-012328
Well 30	WCR2014-007922	Well 62	WCR1998-010945
Well 31	WCR2017-002288	Well 63	WCR2001-015603
Well 32	WCR2018-005473		

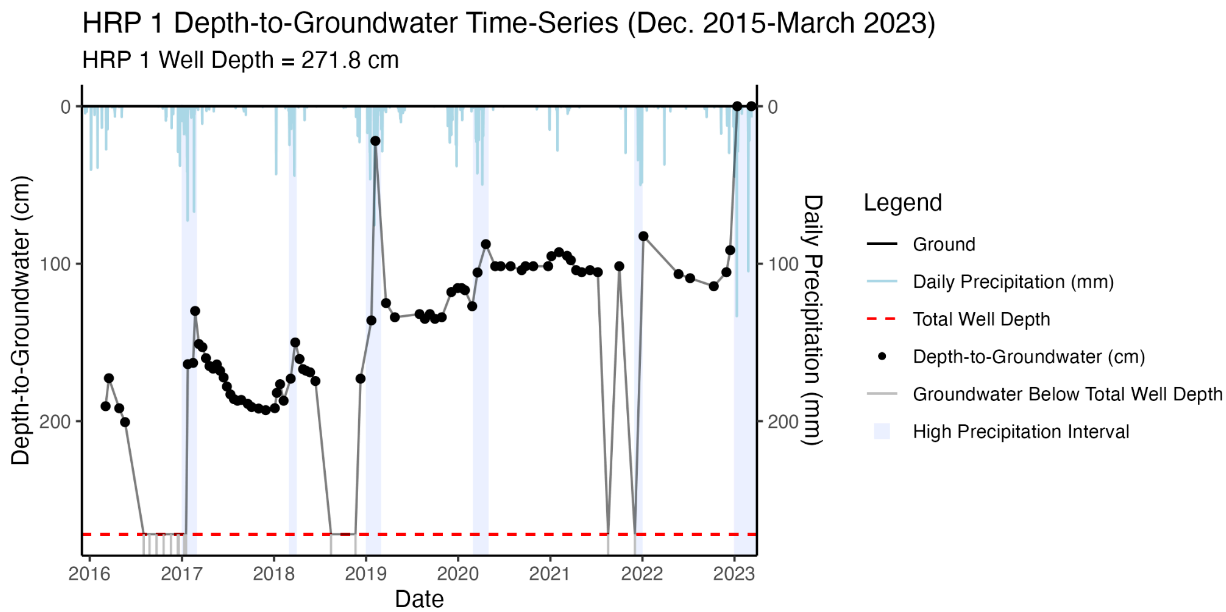
3.2 Hydrology

3.2.1 Time-Series Plots

A. Time-Series Plots for East Grove Shallow Groundwater Monitoring Wells

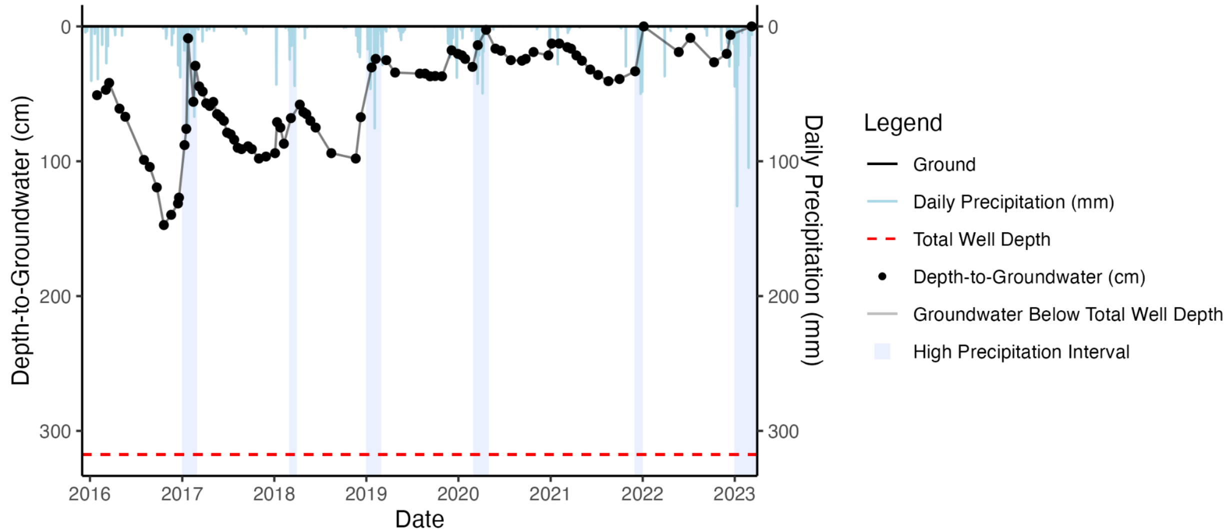
Time-Series Plots of UCSB Shallow Groundwater Monitoring Wells

Hedrick Ranch Preserve



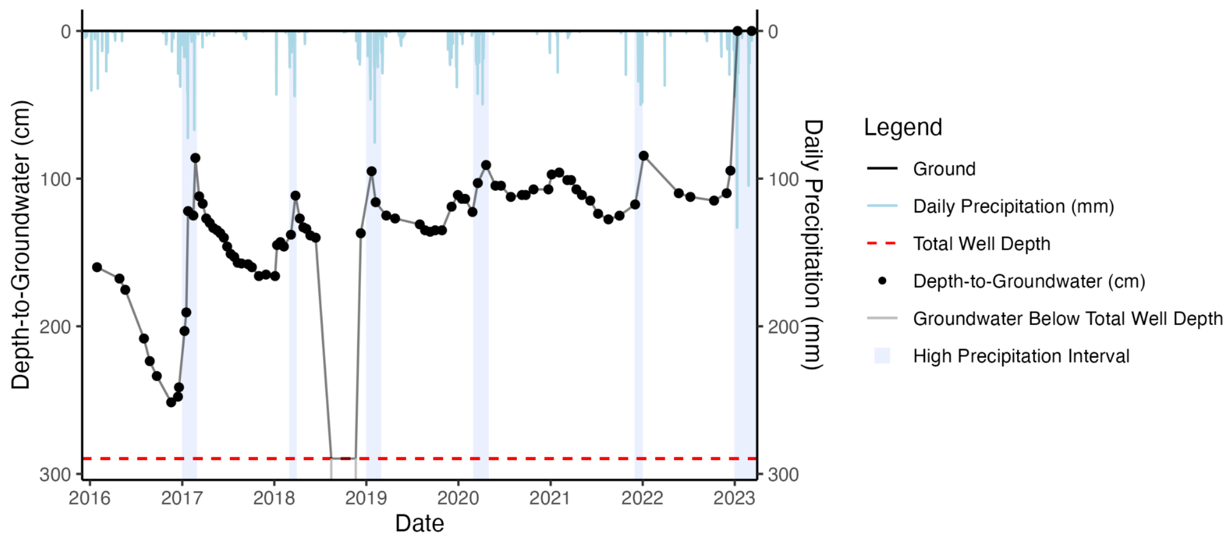
HRP 2 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

HRP 2 Well Depth = 317.5 cm



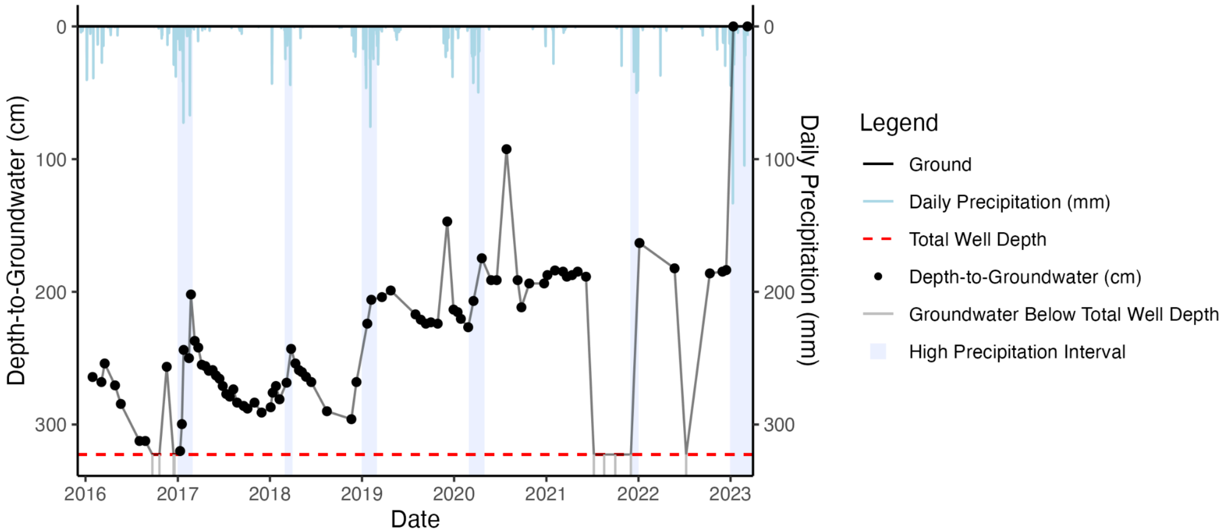
HRP 3 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

HRP 3 Well Depth = 289.6 cm



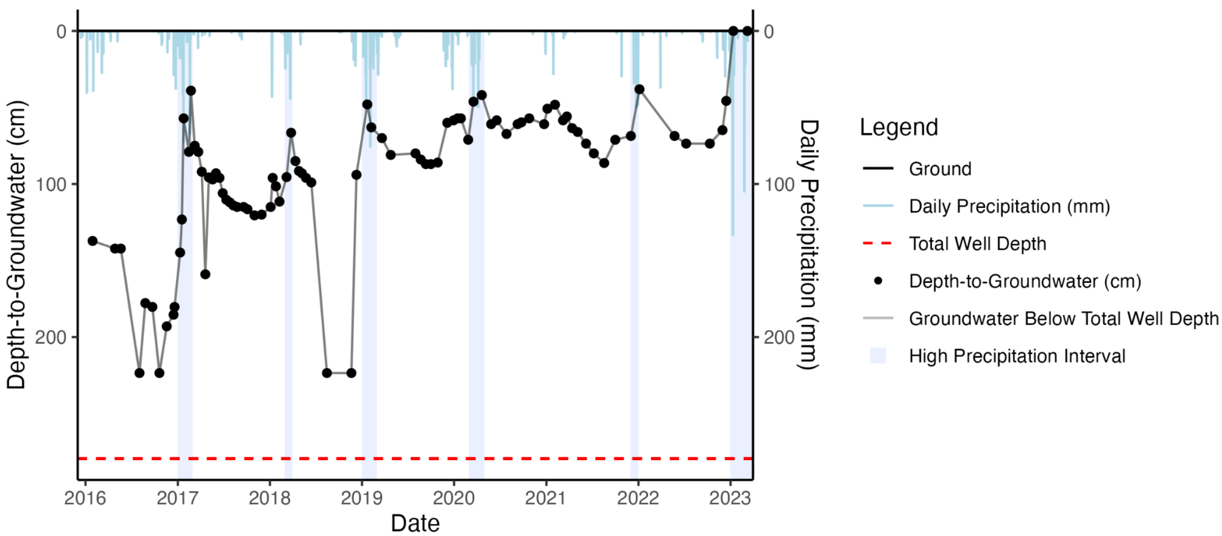
HRP 4 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

HRP 4 Well Depth = 322.6 cm



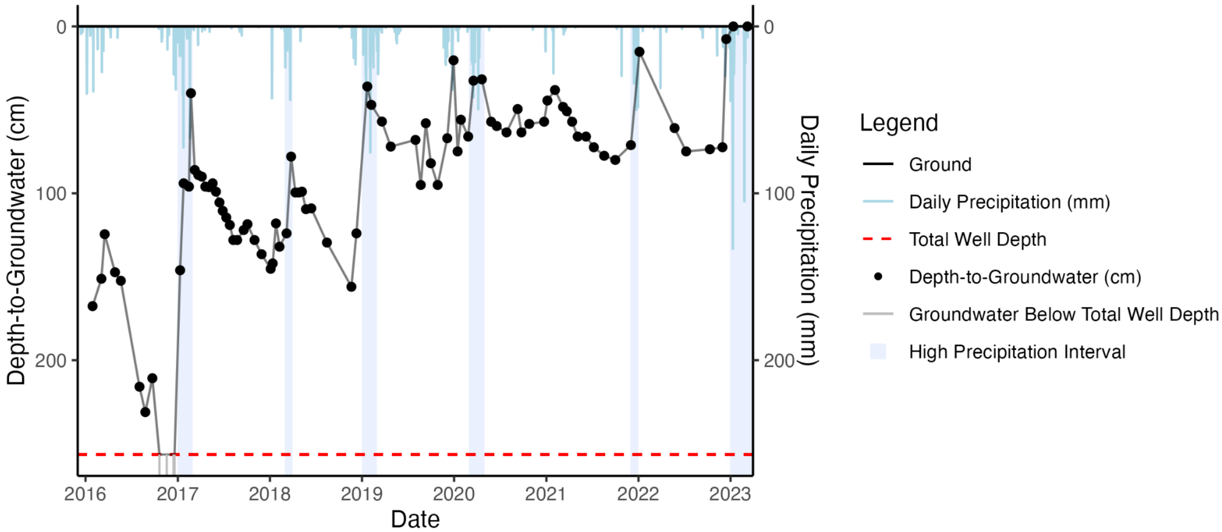
HRP 5 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

HRP 5 Well Depth = 279.4 cm



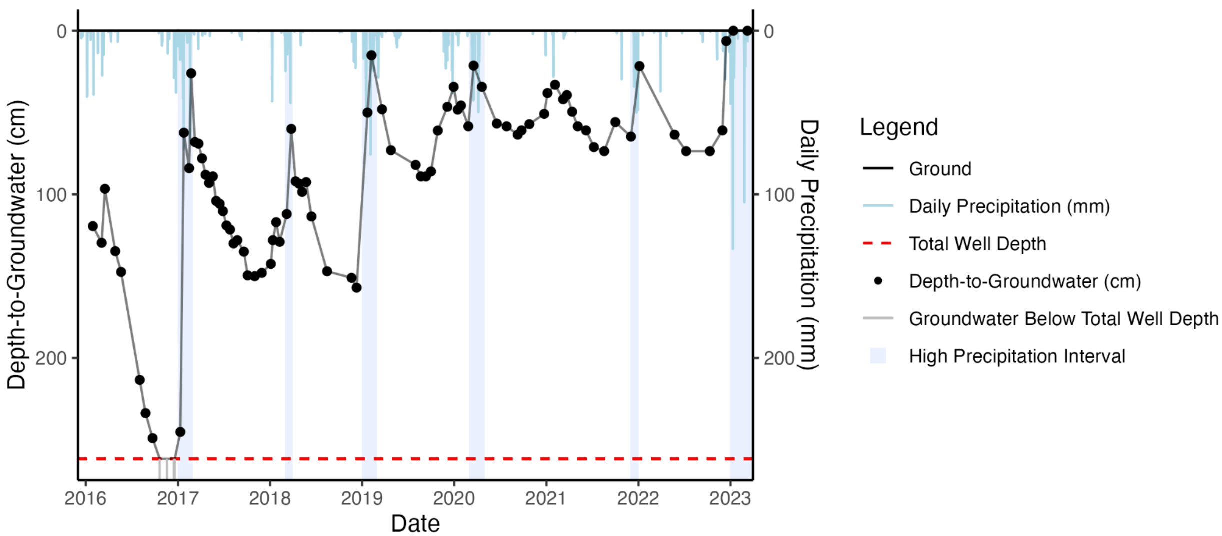
HRP 6 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

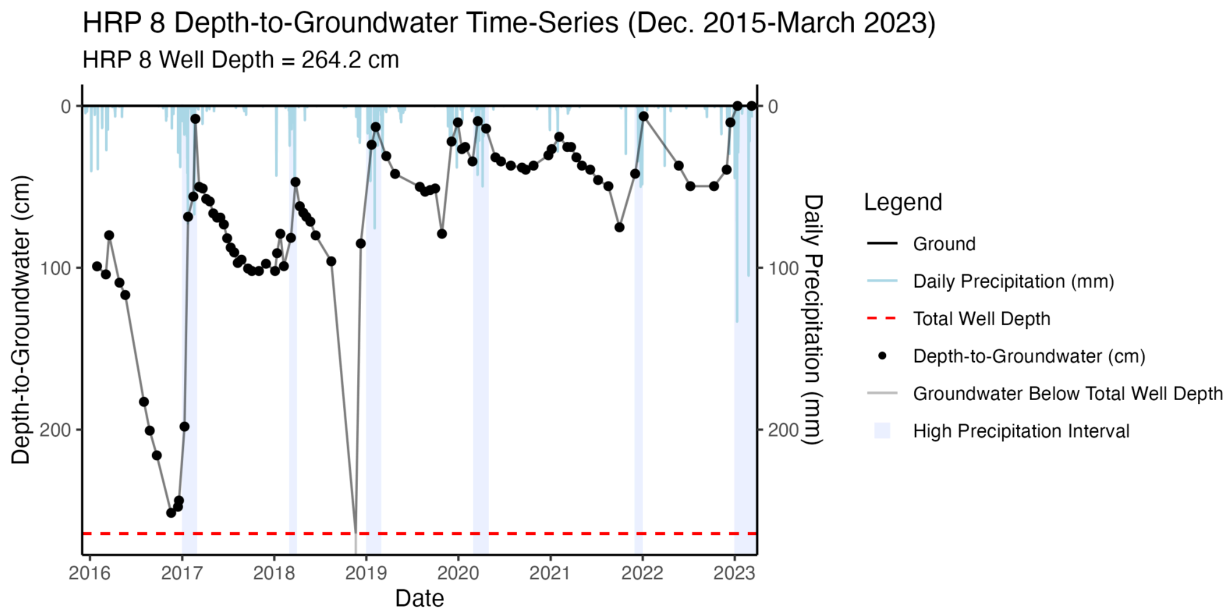
HRP 6 Well Depth = 256.5 cm



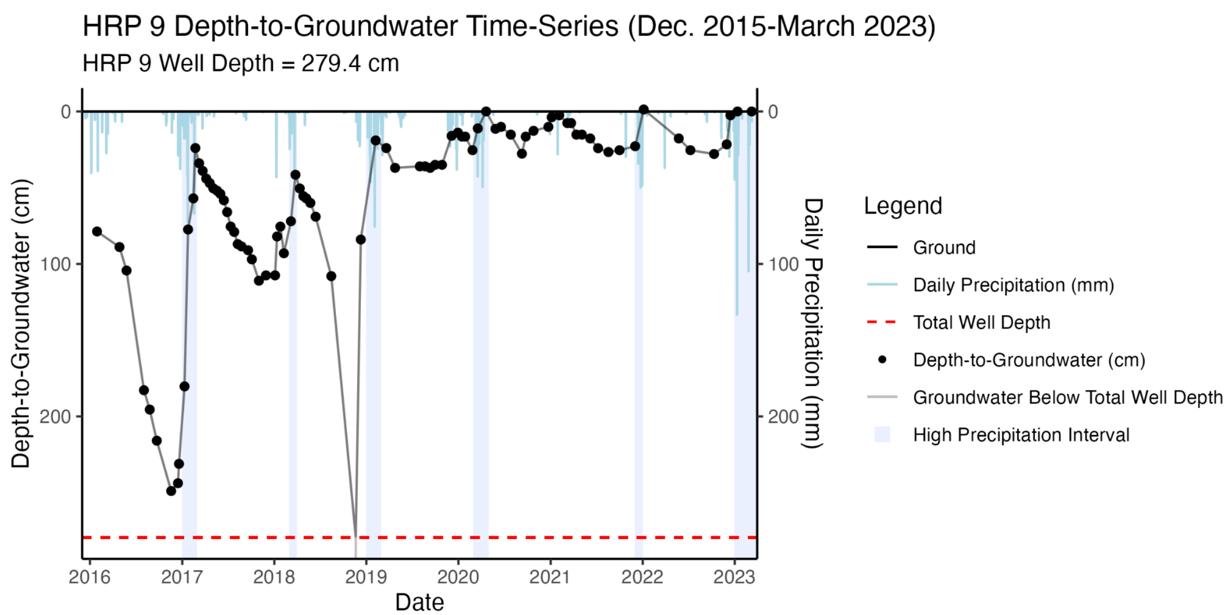
HRP 7 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

HRP 7 Well Depth = 261.6 cm





HRP 8 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)
HRP 8 Well Depth = 264.2 cm
Depth-to-Groundwater (cm)
Daily Precipitation (mm)
Date
0
100
200
2016
2017
2018
2019
2020
2021
2022
2023
Legend
Ground
Daily Precipitation (mm)
Total Well Depth
Depth-to-Groundwater (cm)
Groundwater Below Total Well Depth
High Precipitation Interval

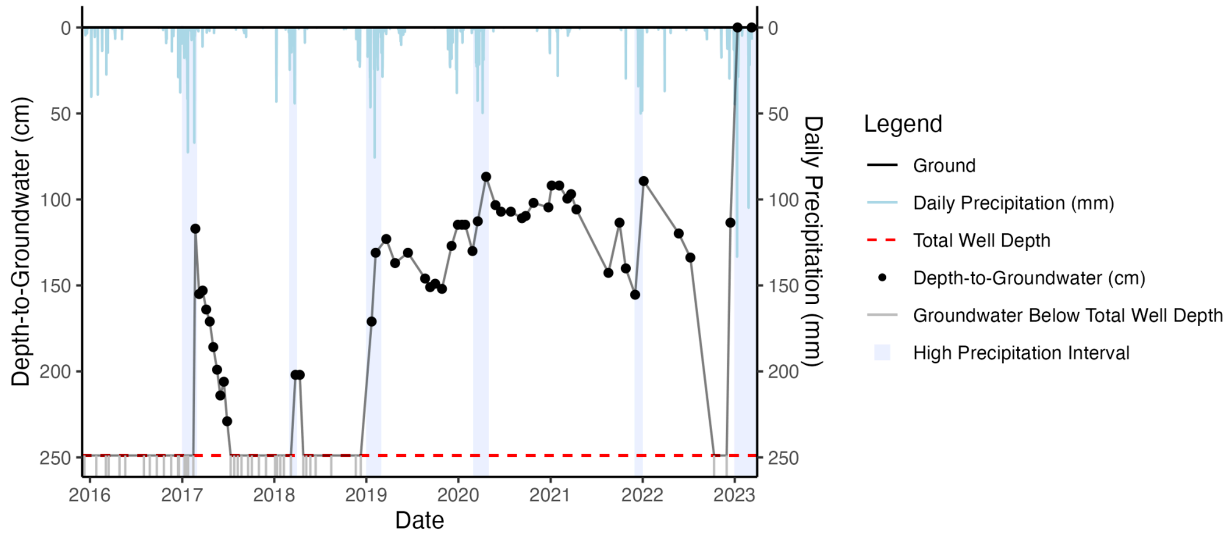


HRP 9 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)
HRP 9 Well Depth = 279.4 cm
Depth-to-Groundwater (cm)
Daily Precipitation (mm)
Date
0
100
200
2016
2017
2018
2019
2020
2021
2022
2023
Legend
Ground
Daily Precipitation (mm)
Total Well Depth
Depth-to-Groundwater (cm)
Groundwater Below Total Well Depth
High Precipitation Interval

Taylor Ranch

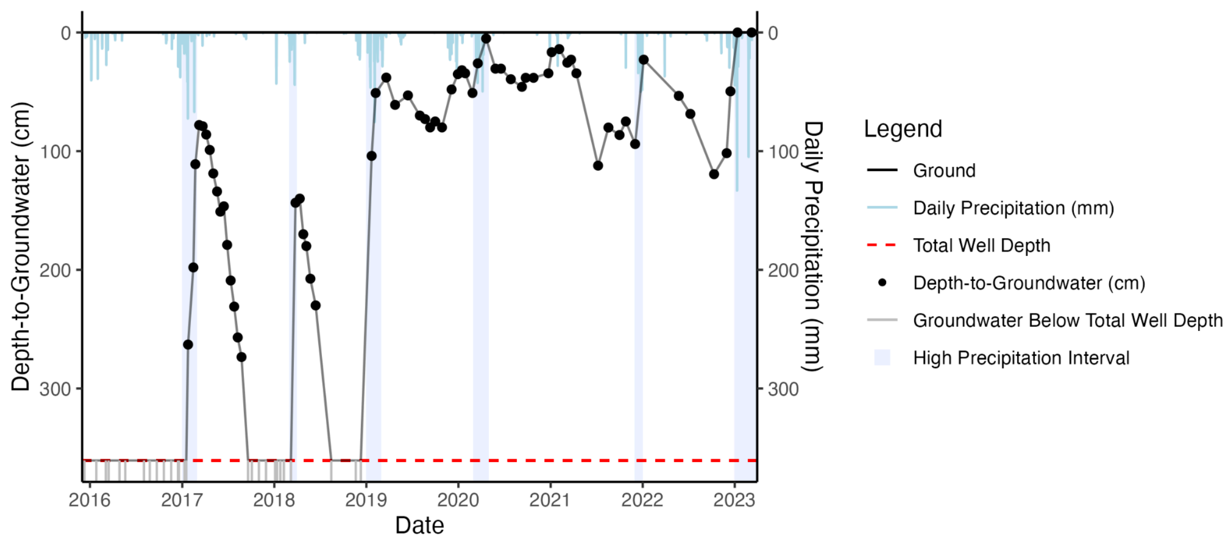
Taylor 1 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

Taylor 1 Well Depth = 248.9 cm



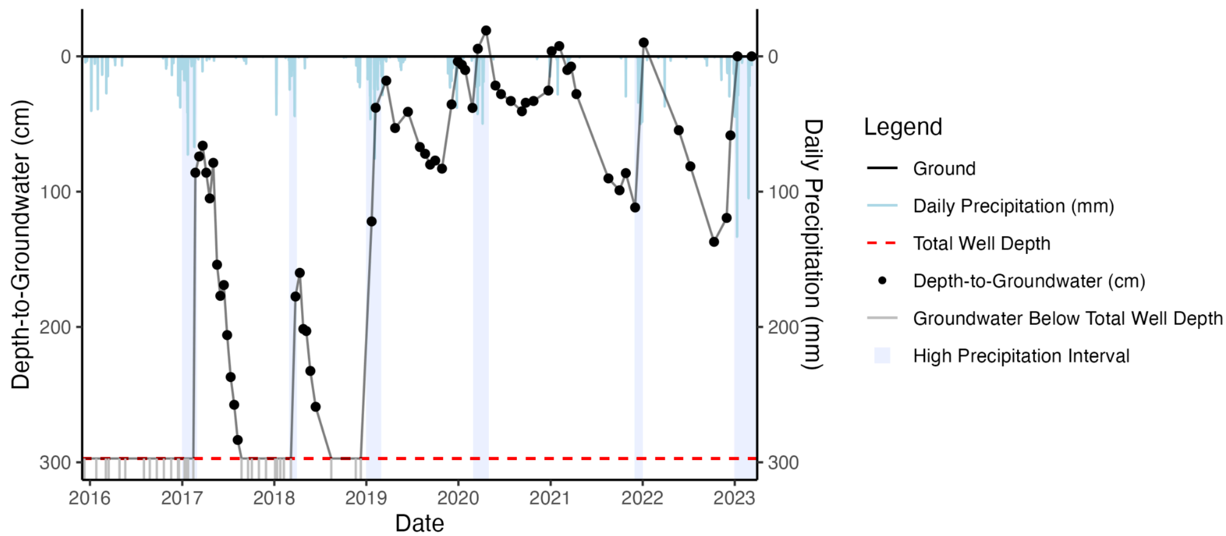
Taylor 2 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

Taylor 2 Well Depth = 360.7 cm



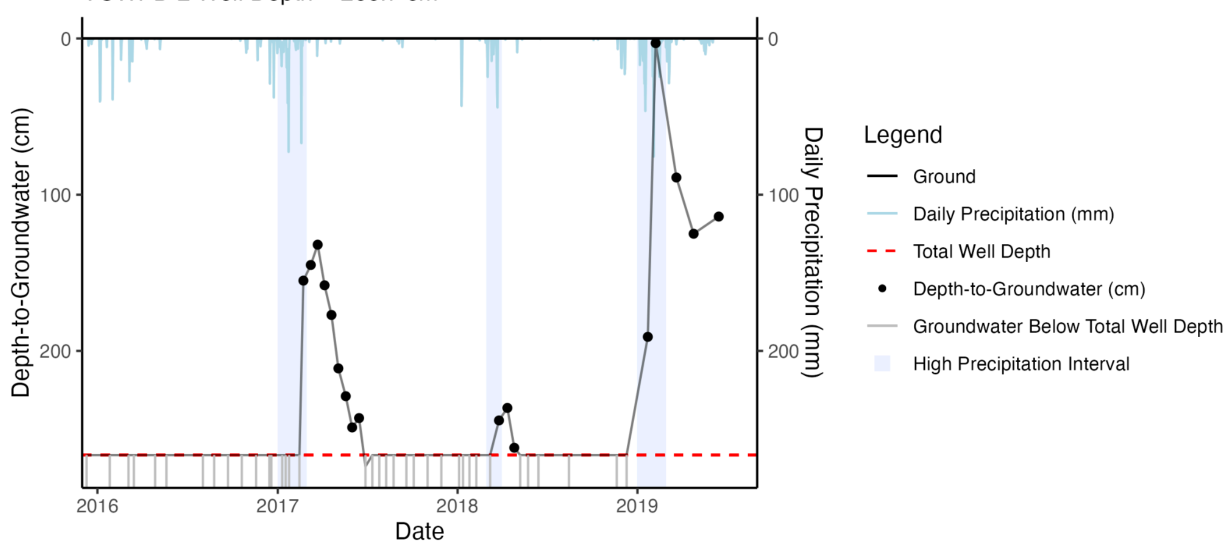
VCWPD 1 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 1 Well Depth = 297.2 cm



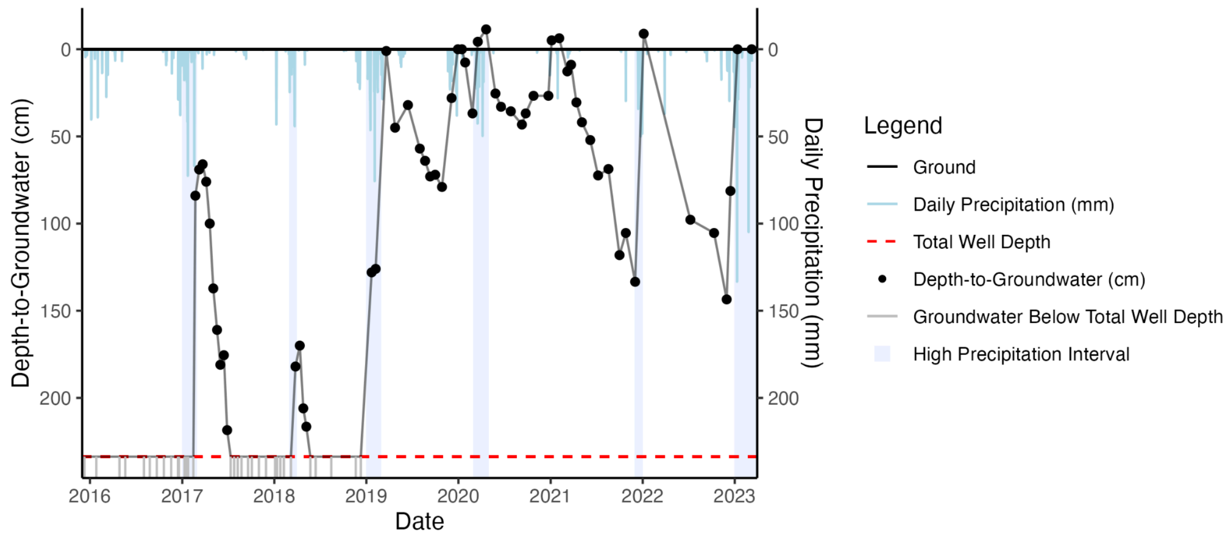
VCWPD 2 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 2 Well Depth = 266.7 cm



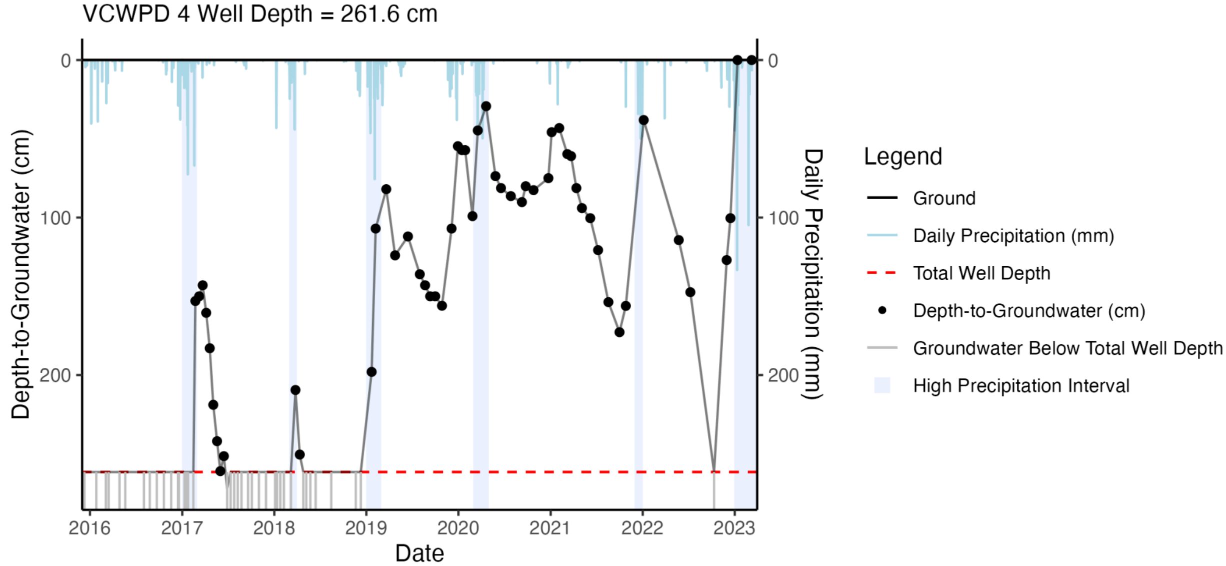
VCWPD 3 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 3 Well Depth = 233.7 cm



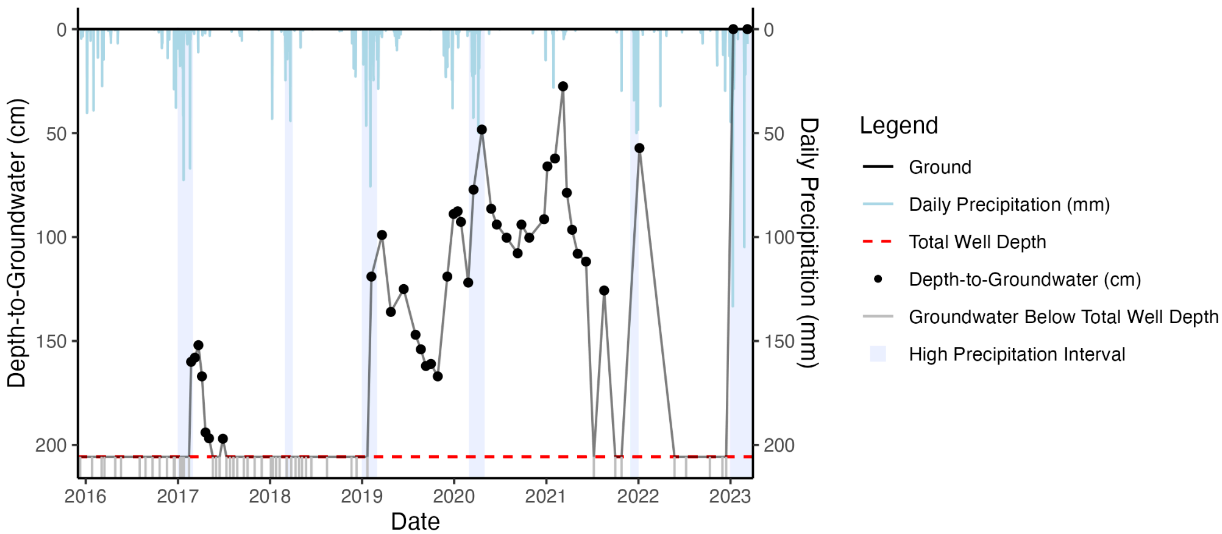
VCWPD 4 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 4 Well Depth = 261.6 cm



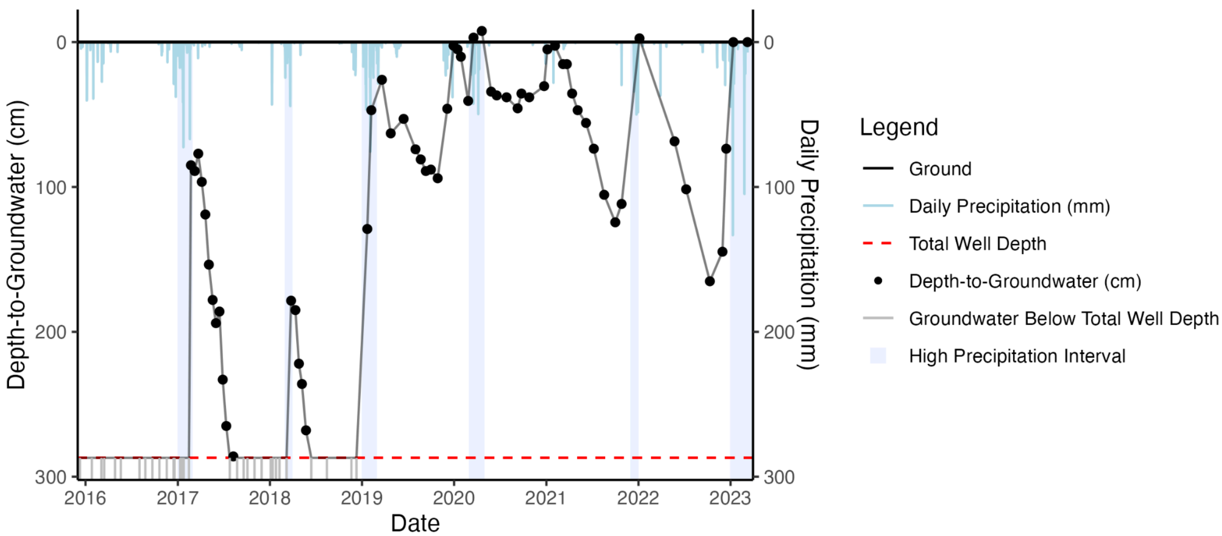
VCWPD 5 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 5 Well Depth = 205.7 cm



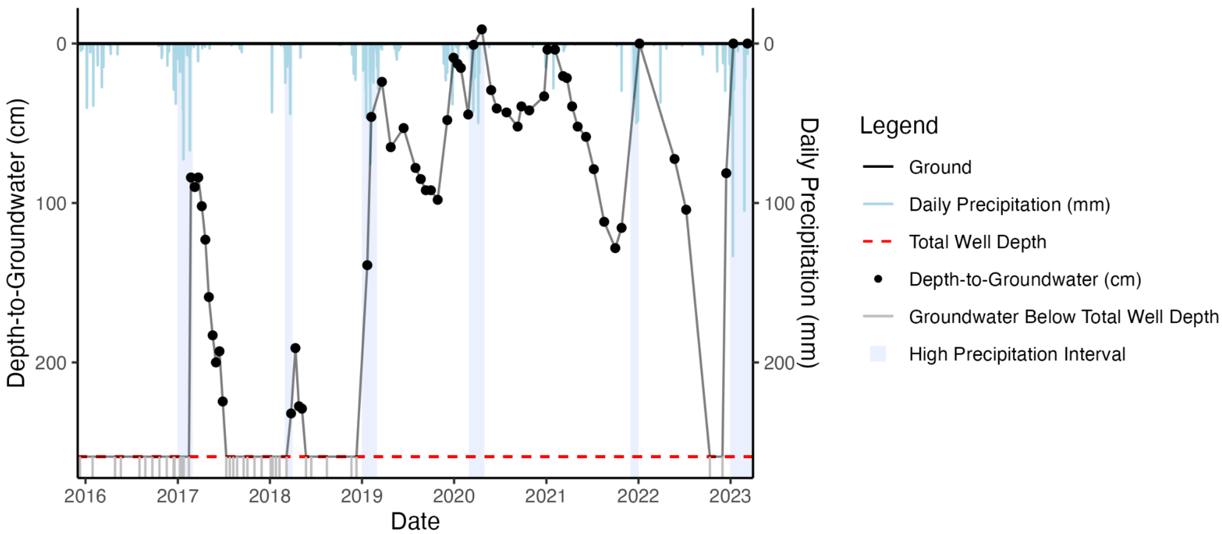
VCWPD 6 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 6 Well Depth = 287 cm



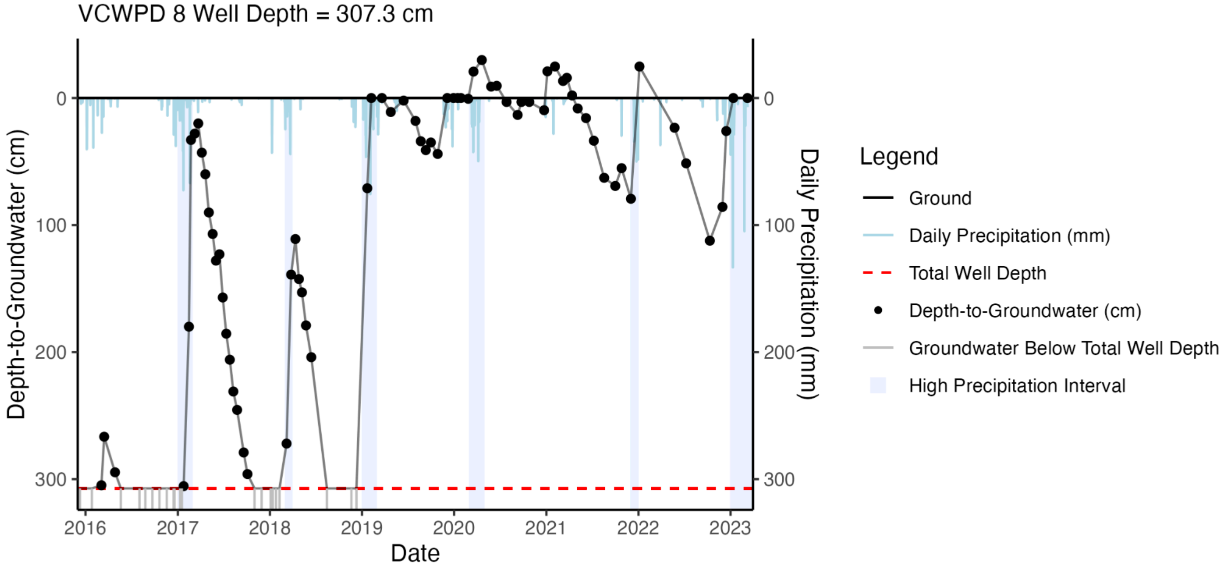
VCWPD 7 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

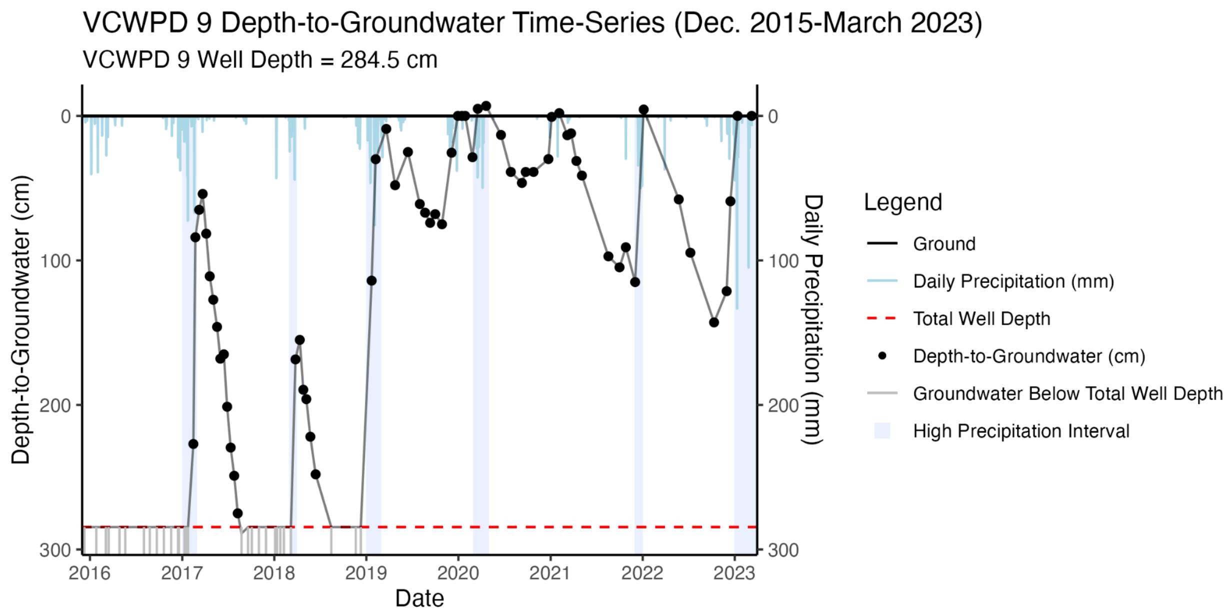
VCWPD 7 Well Depth = 259.1 cm

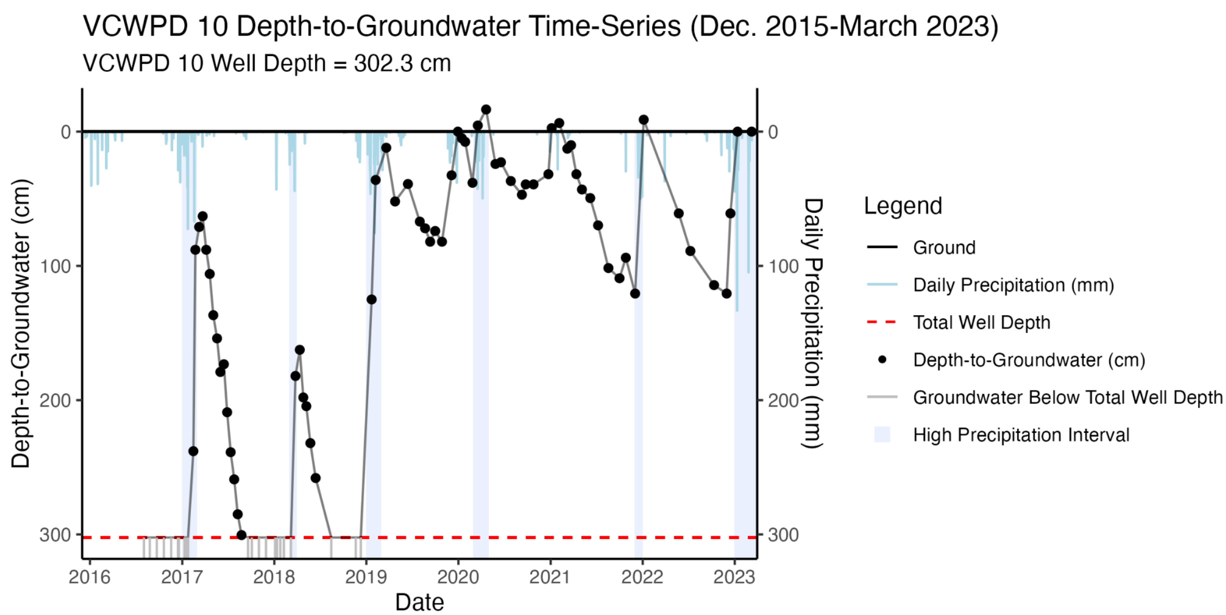


VCWPD 8 Depth-to-Groundwater Time-Series (Dec. 2015-March 2023)

VCWPD 8 Well Depth = 307.3 cm







B. Time-Series Plots of Fillmore Subbasin Wells by Category

Date Range Exception:

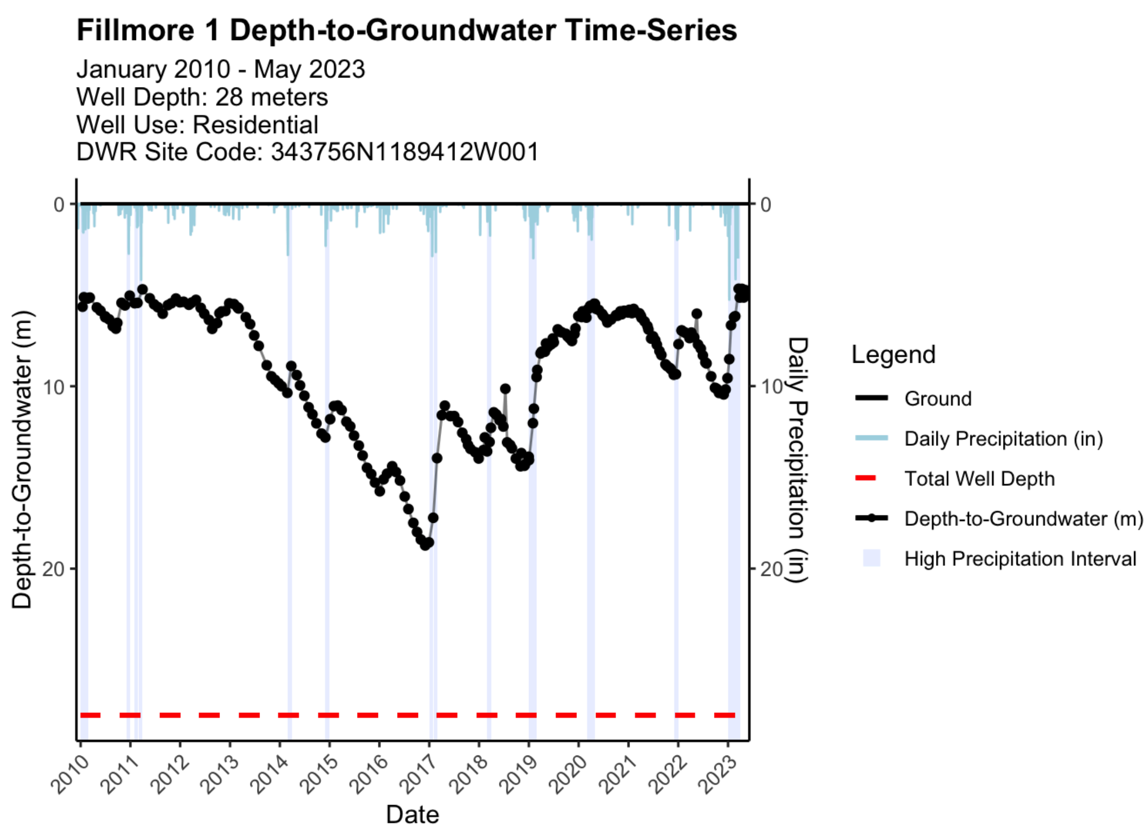
All Fillmore subbasin time series graphs had a date range of 2010 to 2023 with one exception for the Fillmore 9 well. An exception was made for Fill 9 to change the x-axis scale to range from 2015 to 2023 since this well had 8 out of 9 years where there were at least 16 measurements taken in those 8 years. The breakdown of Fill 9's number of recorded measurements each year is: 17(2015),16(2016), 18(2017), 36(2018) 26(2019) 22(2020), 22(2021), 18(2022), 6(2023).

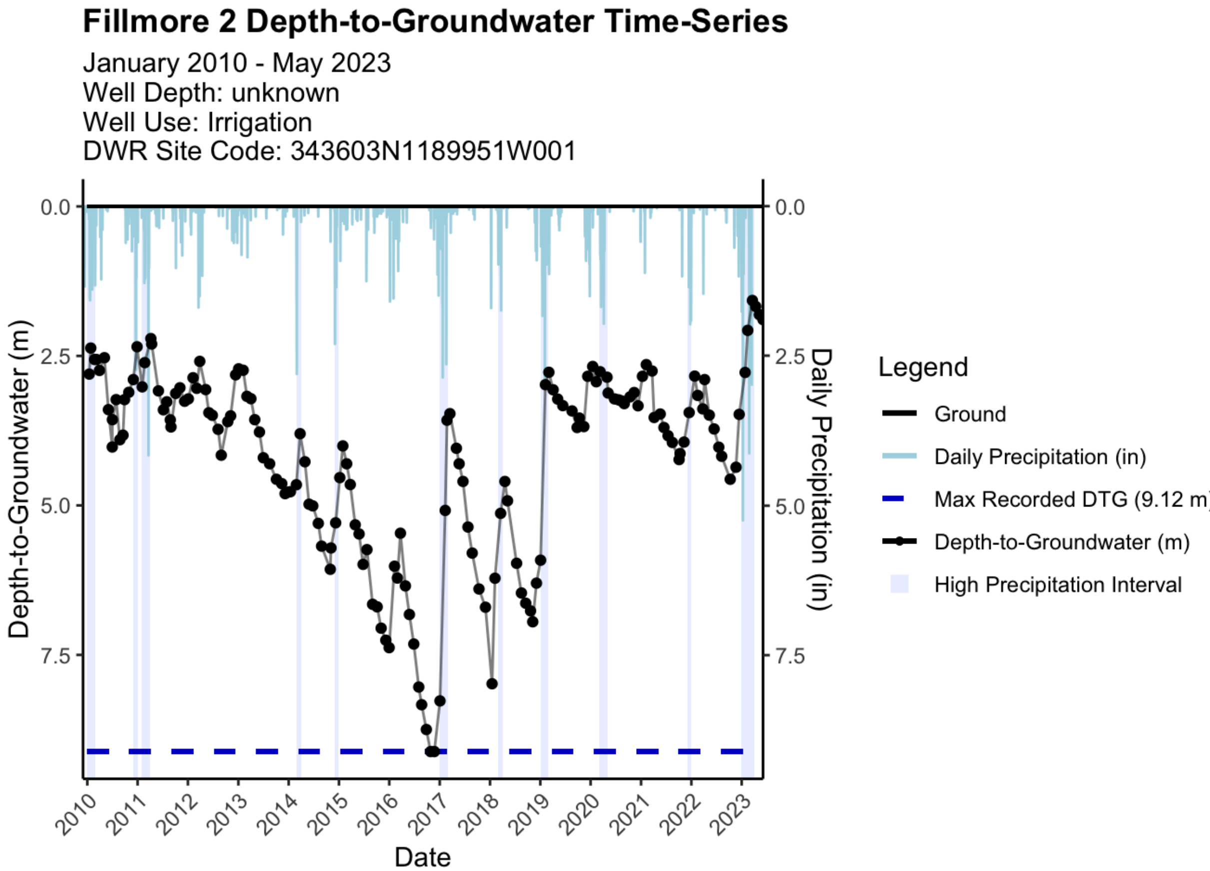
Total Well Depth Exceptions:

There were some wells whose known total well depth greatly exceeded the maximum ("deepest") depth to groundwater (DTG) measurements. This skewed the visual representation of these wells. Therefore, for wells whose known total well depth was over 100 meters (~328 feet) from their respective maximum depth to groundwater measurement, we used a green dashed line at the bottom of the graph to represent the maximum recorded depth to groundwater (as opposed to the red dashed line representing the true total well depth, or the blue dashed line representing the maximum depth to groundwater when the true well depth was not known) and provided the known total well depth in the subtitles of the graph. An example of this exeption can be seen in the Fillmore 10 time series graph.

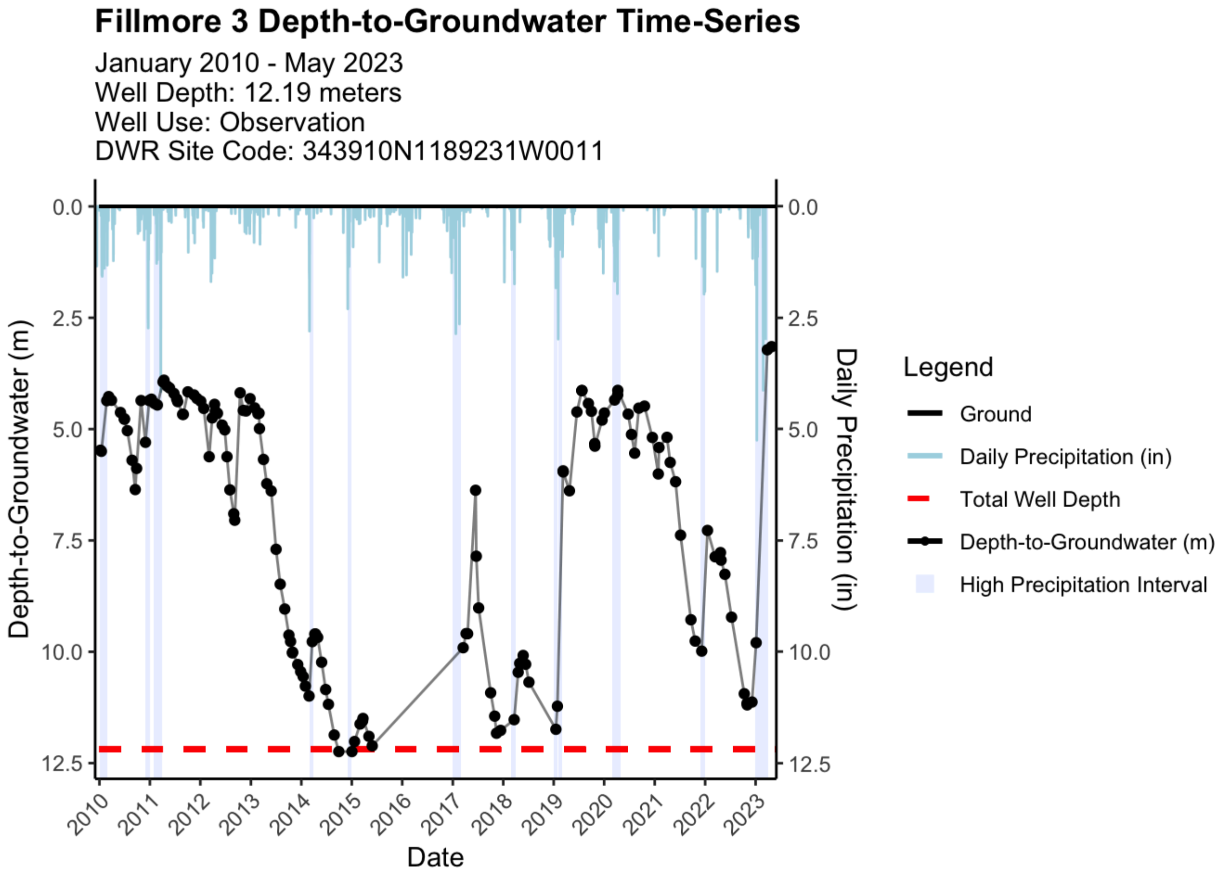
Category: Best

Specification: Wells that have 10 or more measurements per year over a course of at least 9 years during the time period of 2010 to 2023





Fillmore 2 Depth-to-Groundwater Time-Series
January 2010 - May 2023
Well Depth: unknown
Well Use: Irrigation
DWR Site Code: 343603N1189951W001
Depth-to-Groundwater (m)
Daily Precipitation (in)
0.0
2.5
5.0
7.5
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Date
Legend
Ground
Daily Precipitation (in)
Max Recorded DTG (9.12 m)
Depth-to-Groundwater (m)
High Precipitation Interval

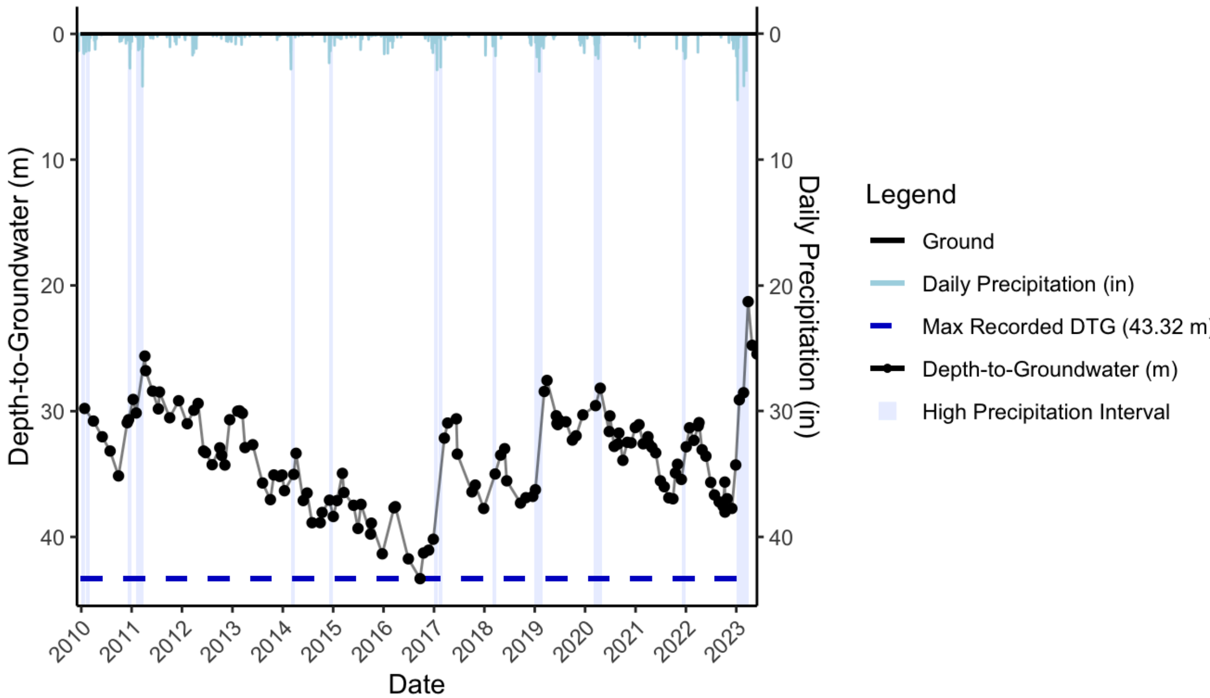


Category: Good

Specification: Wells that have 8 or 9 measurements per year over a course of at least 9 years during the time period 2010 to 2023

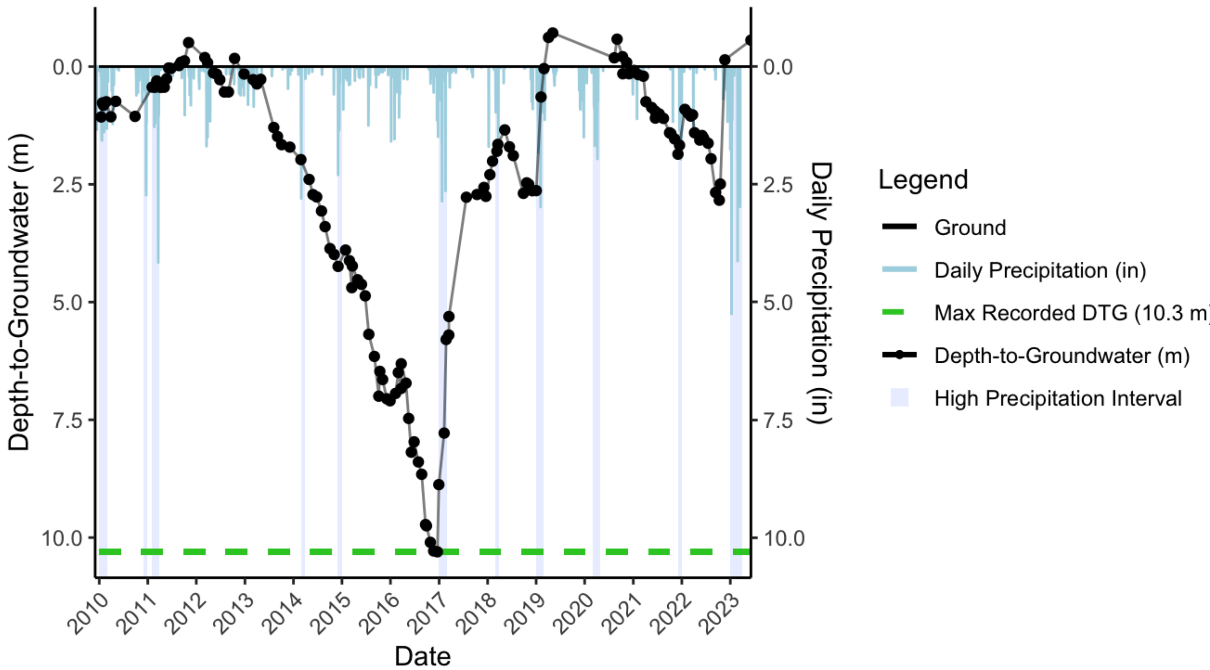
Fillmore 4 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: unknown
Well Use: Unknown
DWR Site Code: 344195N1189306W001



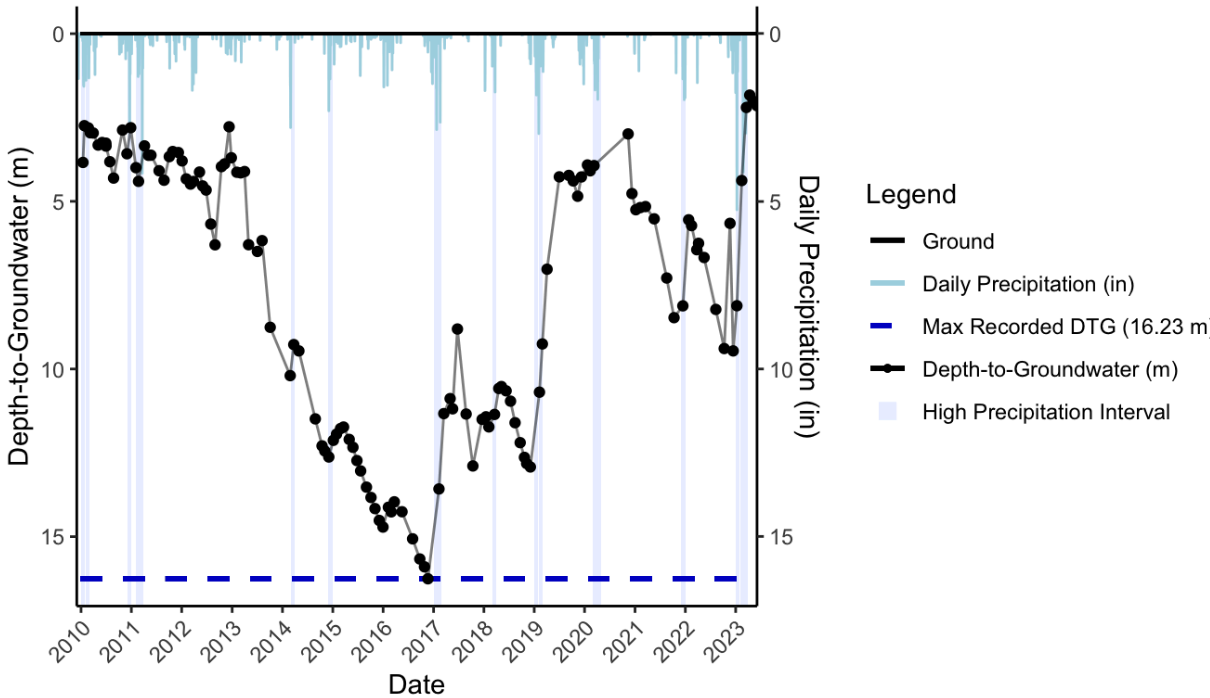
Fillmore 5 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: 157.89 meters
Max Recorded DTG: 10.3 meters
Well Use: Irrigation
DWR Site Code: 343919N1188820W001



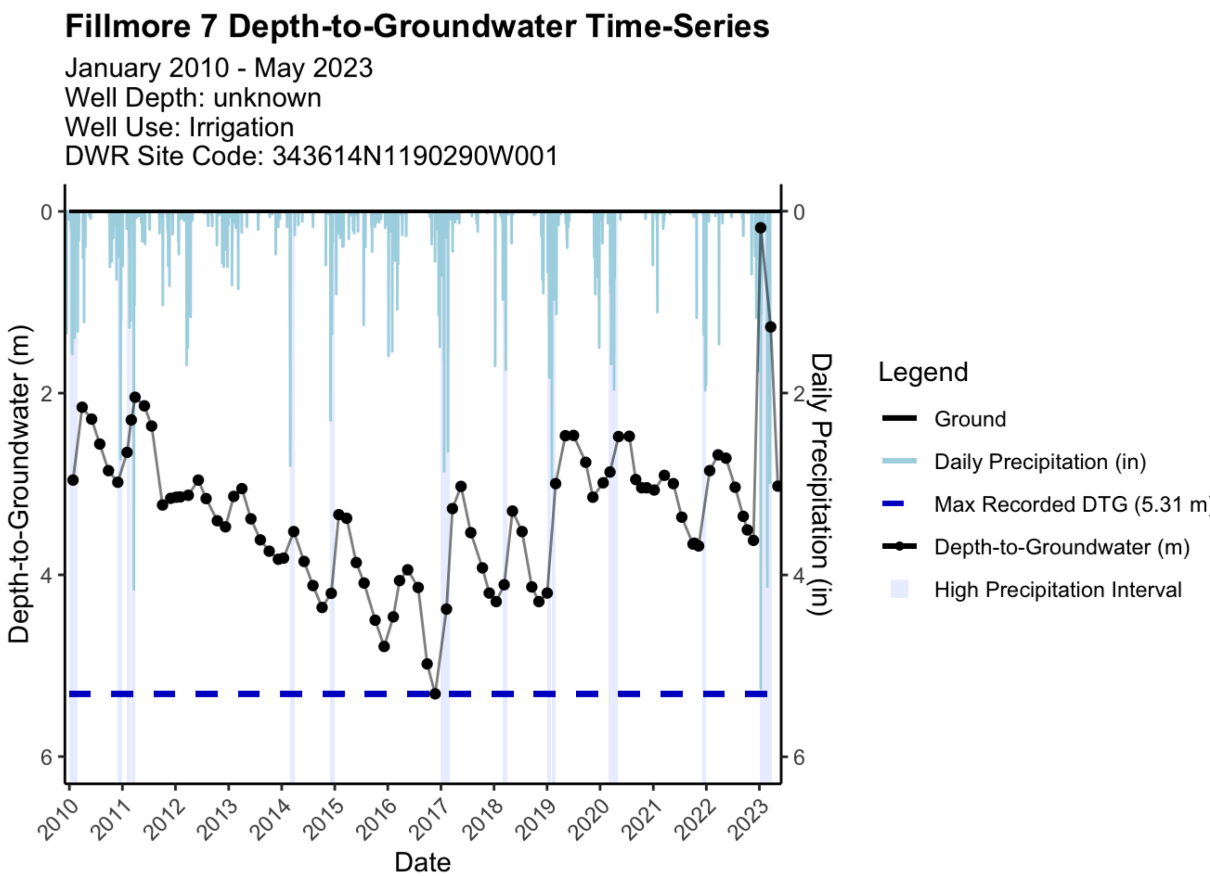
Fillmore 6 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: unknown
Well Use: Irrigation
DWR Site Code: 343864N1189159W001



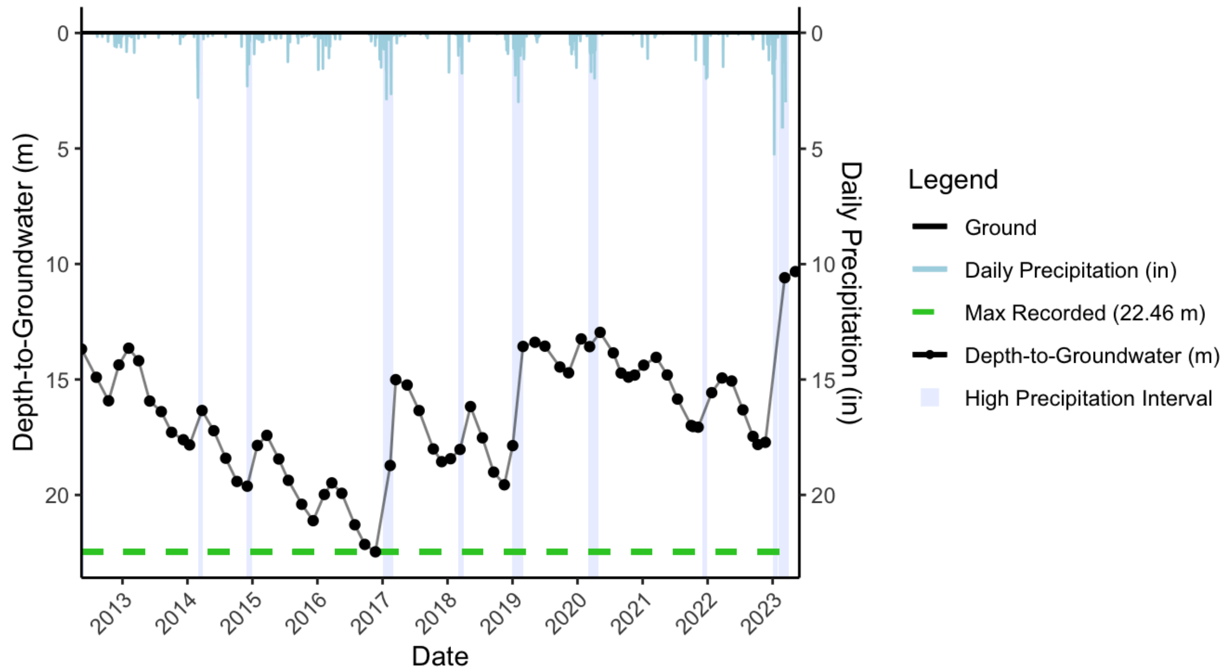
Category: Okay

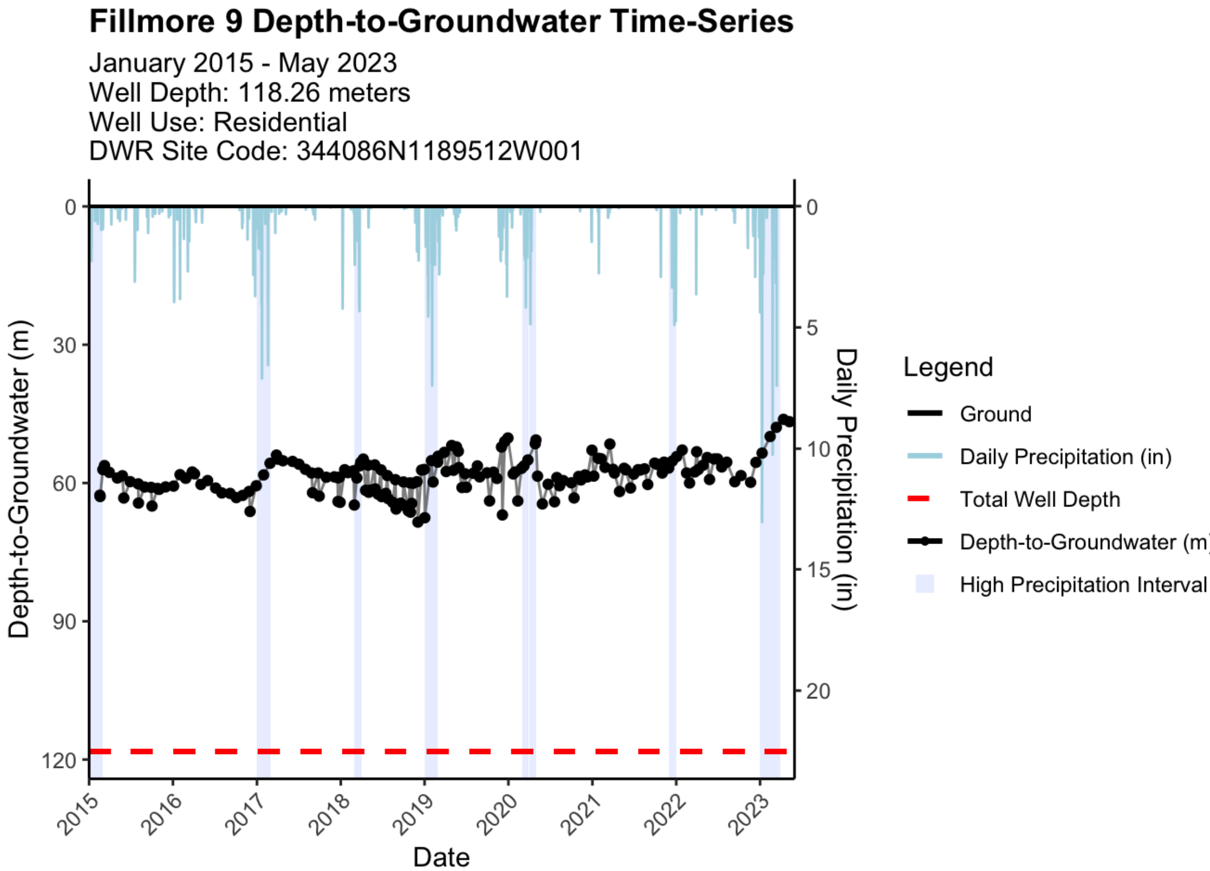
Specification: Wells that have 6 or 7 measurements per year over the course of at least 9 years during the time period of 2010 to 2023.

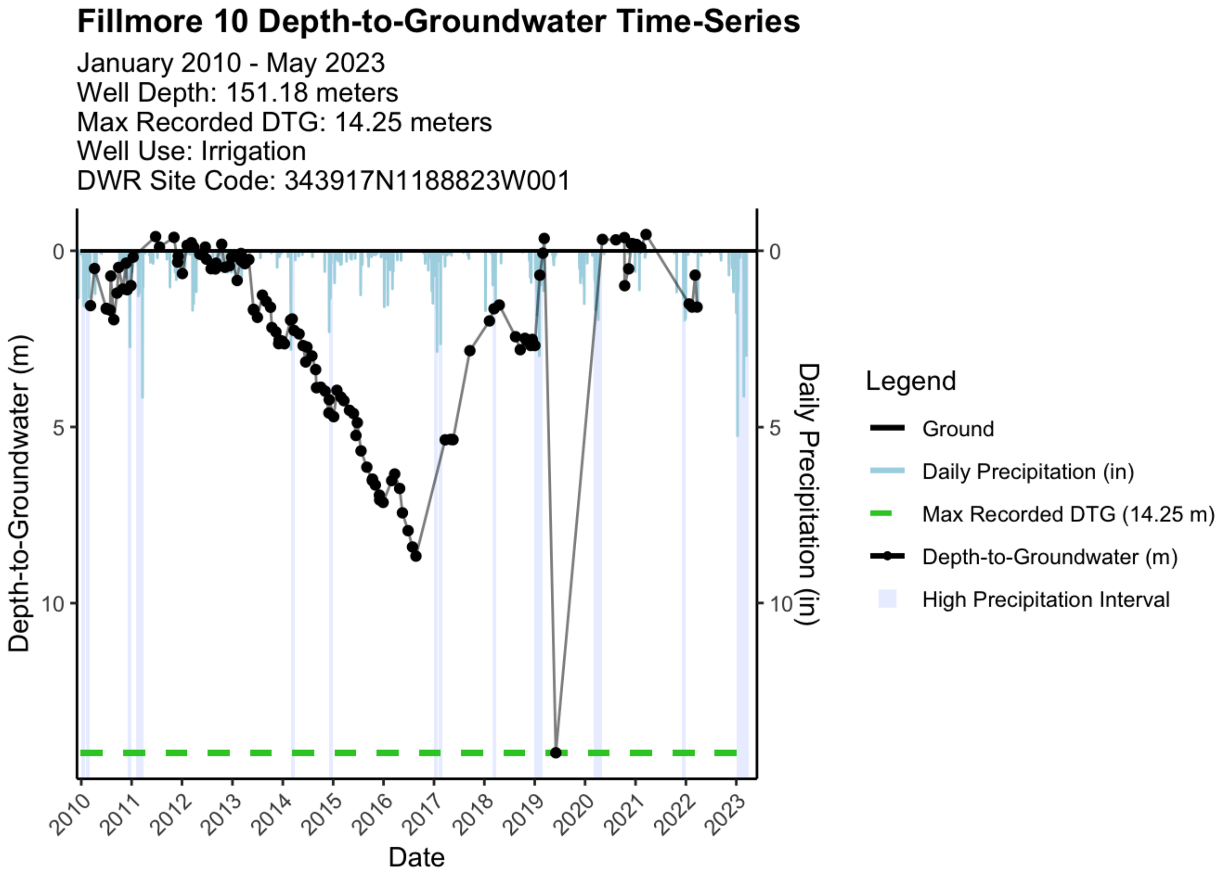


Fillmore 8 Depth-to-Groundwater Time-Series

May 2012 - May 2023
Total Well Depth: 123.14 meters
Max Recorded DTG: 22.46 meters
Well Use: Irrigation
DWR Site Code: 343986N1189487W001



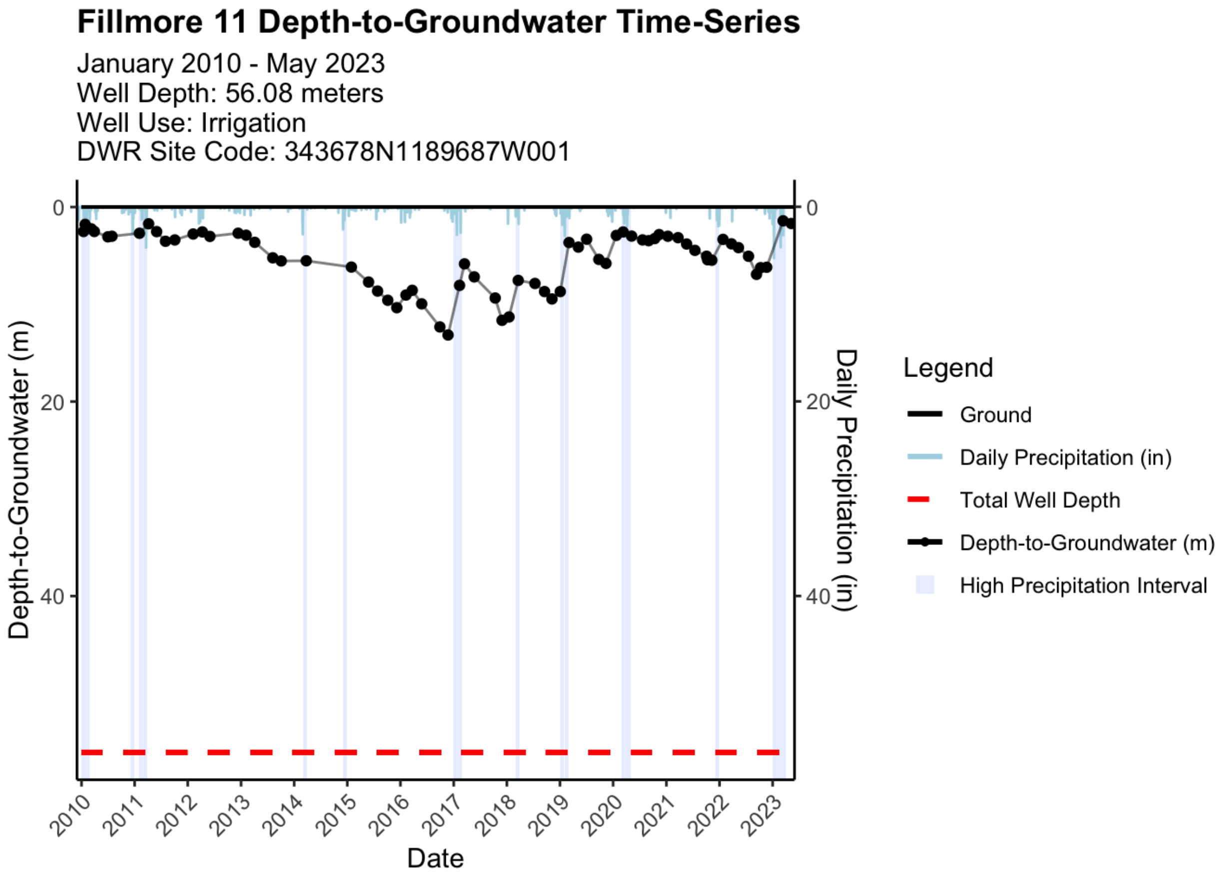

Fillmore 9 Depth-to-Groundwater Time-Series
January 2015 - May 2023
Well Depth: 118.26 meters
Well Use: Residential
DWR Site Code: 344086N1189512W001
Depth-to-Groundwater (m)
0
30
60
90
120
Daily Precipitation (in)
0
5
10
15
20
2015
2016
2017
2018
2019
2020
2021
2022
2023
Date
Legend
Ground
Daily Precipitation (in)
Total Well Depth
Depth-to-Groundwater (m)
High Precipitation Interval



Fillmore 10 Depth-to-Groundwater Time-Series
January 2010 - May 2023
Well Depth: 151.18 meters
Max Recorded DTG: 14.25 meters
Well Use: Irrigation
DWR Site Code: 343917N1188823W001
Depth-to-Groundwater (m)
Daily Precipitation (in)
Date
Legend
Ground
Daily Precipitation (in)
Max Recorded DTG (14.25 m)
Depth-to-Groundwater (m)
High Precipitation Interval

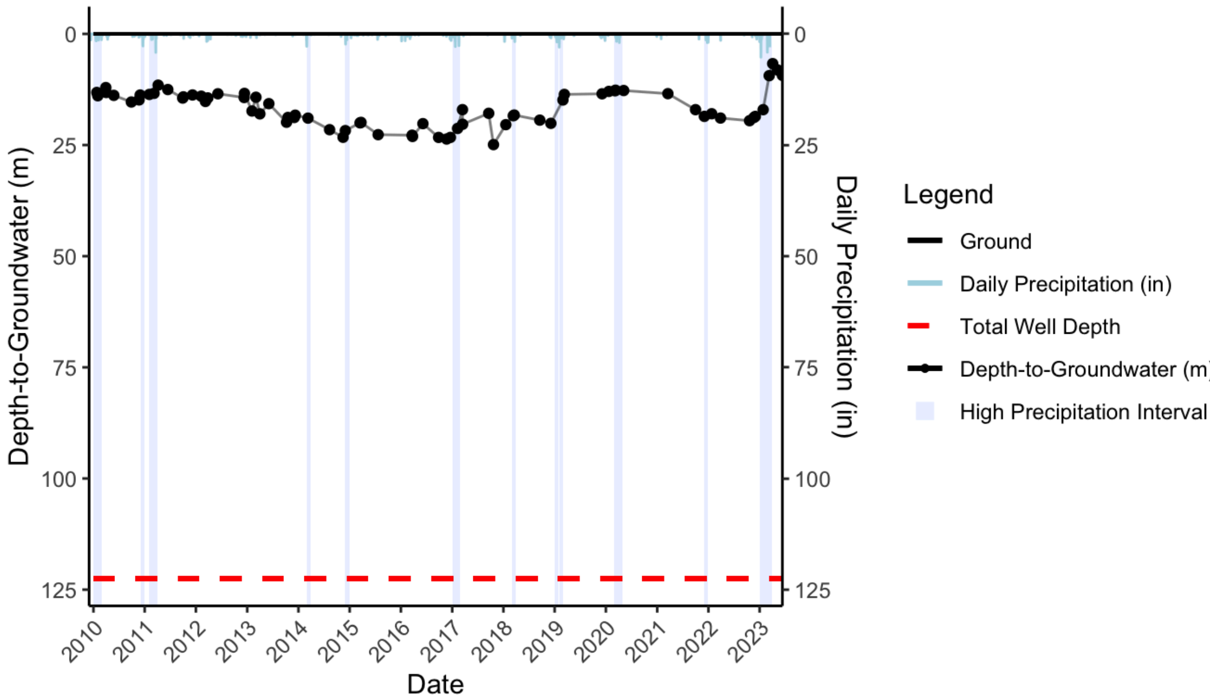
Category: Poor

Specification: Wells that have 3 or 4 measurements per year over the course of at least 9 years during the time period of 2010 to 2023.



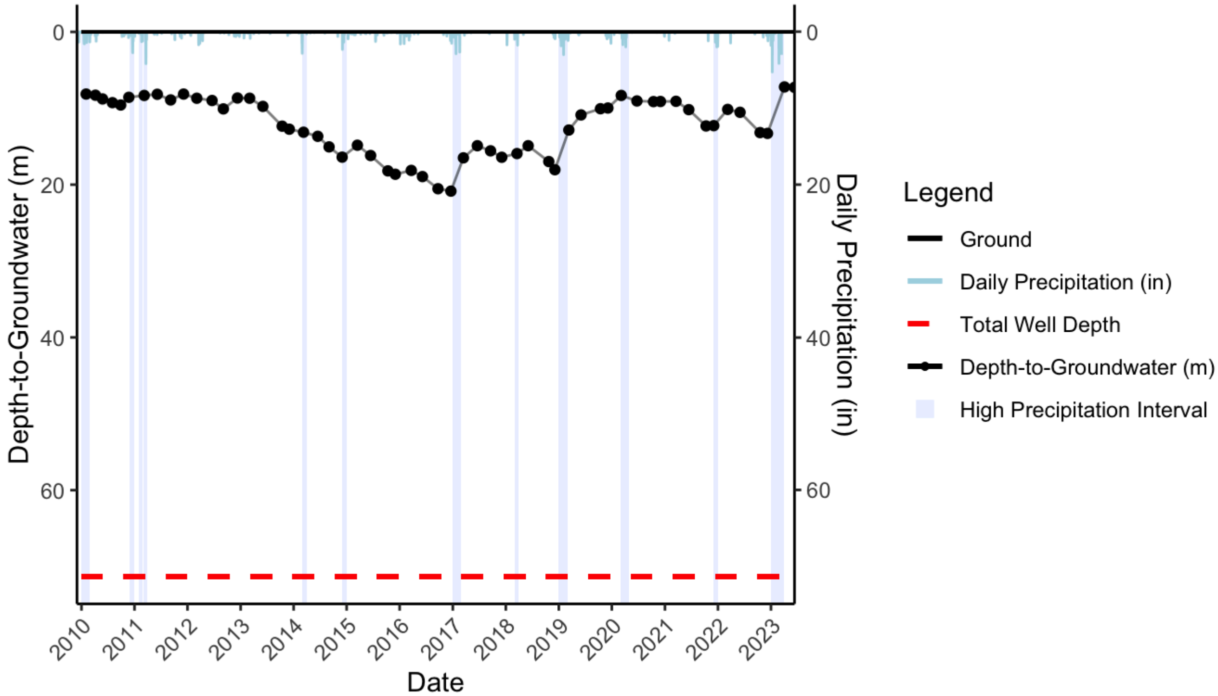
Fillmore 12 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: 122.53 m
Well Use: Irrigation
DWR Site Code: 344056N1189195W001



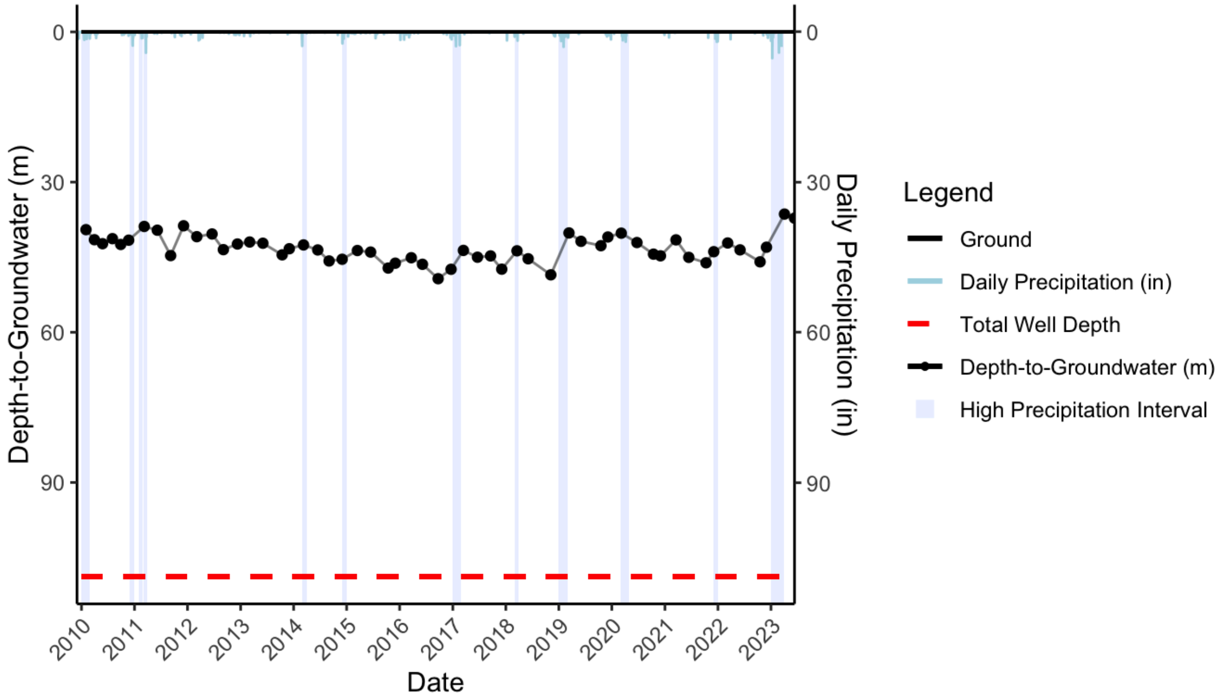
Fillmore 13 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: 71.32 meters
Well Use: Irrigation
DWR Site Code: 343789N1189312W001



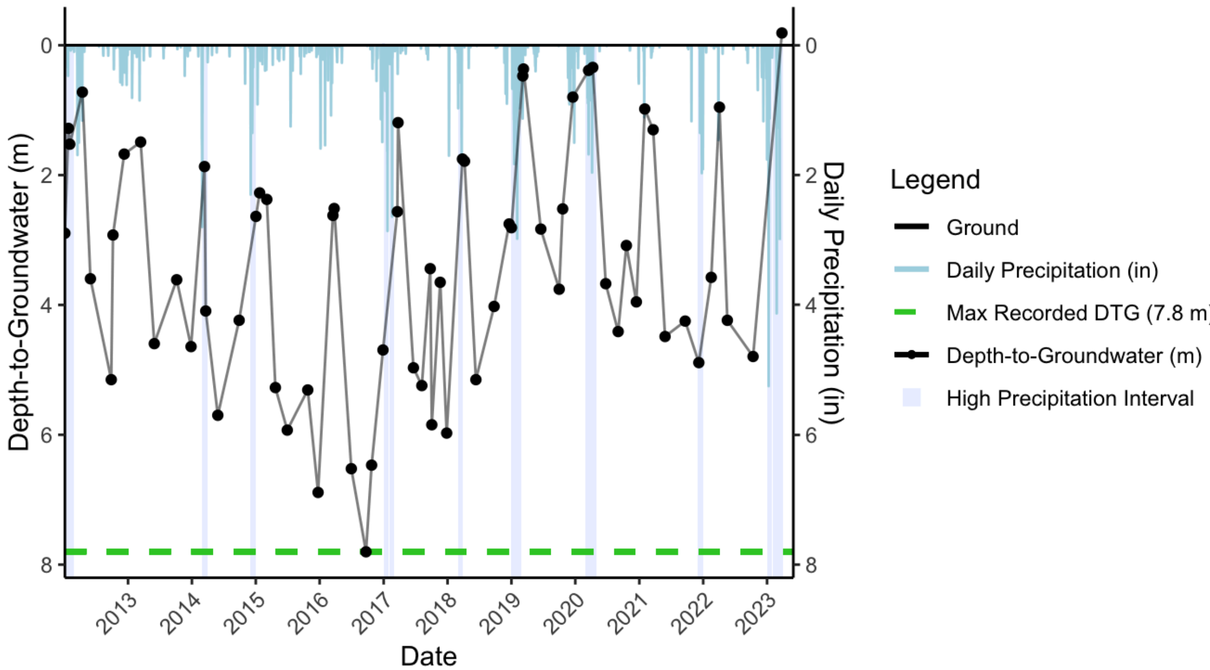
Fillmore 14 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: 108.81 meters
Well Use: Irrigation
DWR Site Code: 343753N1190062W001



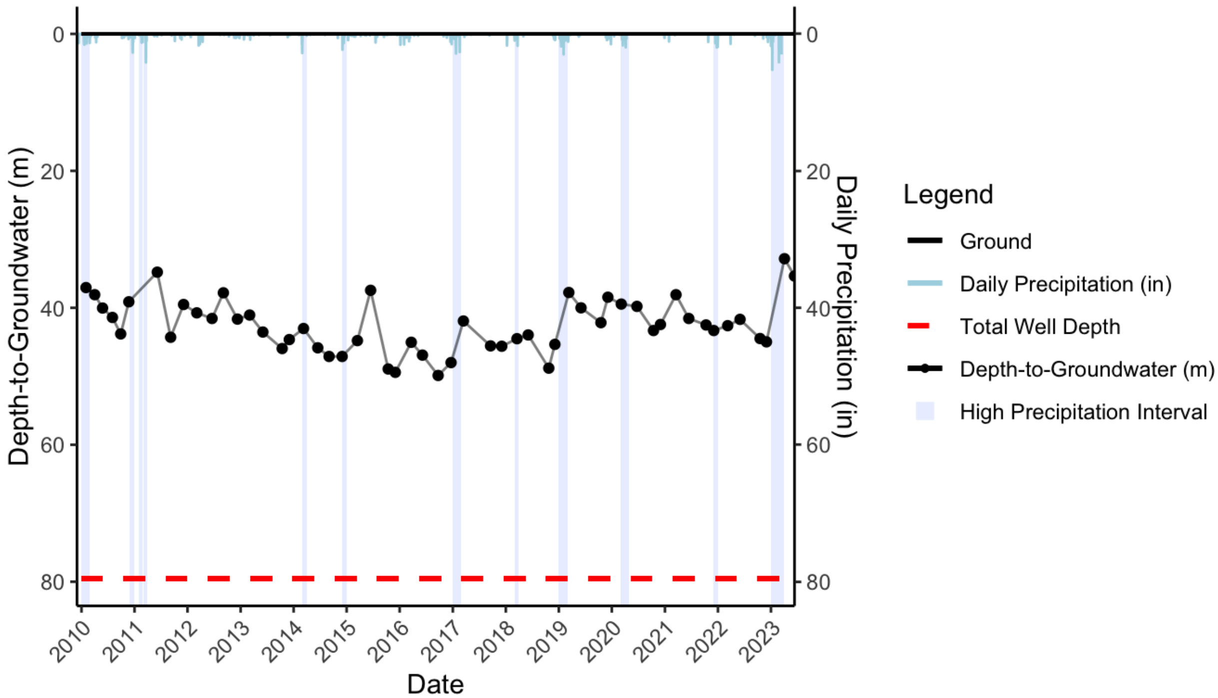
Fillmore 15 Depth-to-Groundwater Time-Series

January 2012 - May 2023
Well Depth: 109.73 m
Max Recorded DTG: 7.8 meters
Well Use: Irrigation
DWR Site Code: 343625N1190323W001



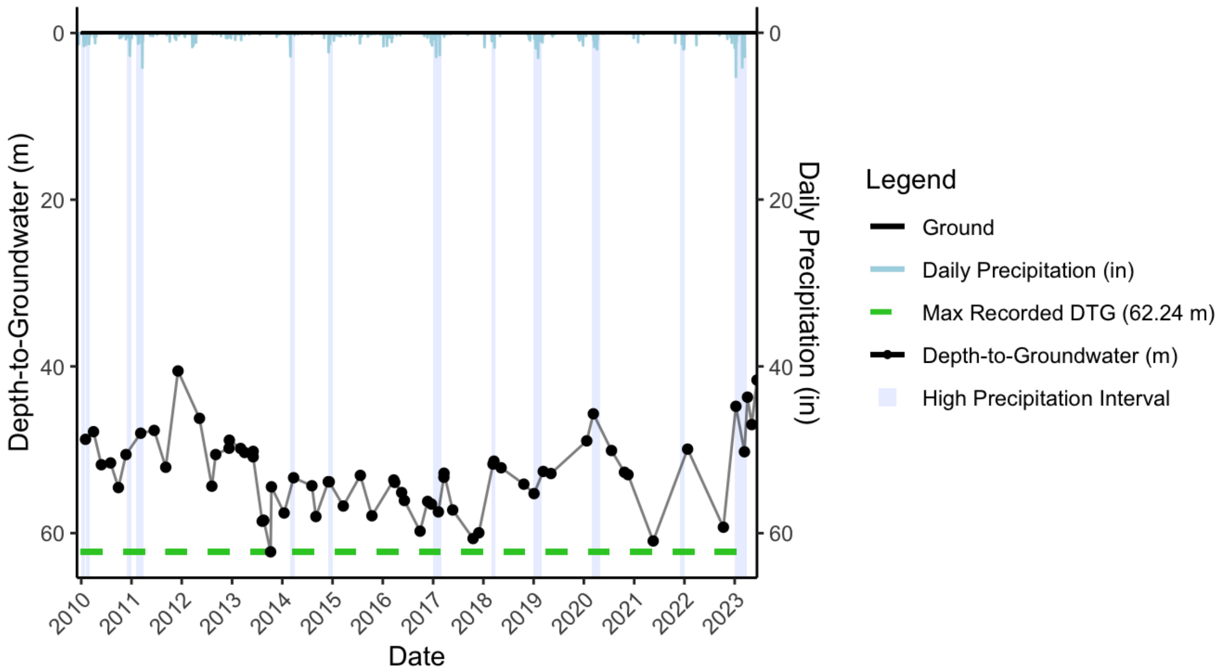
Fillmore 16 Depth-to-Groundwater Time-Series

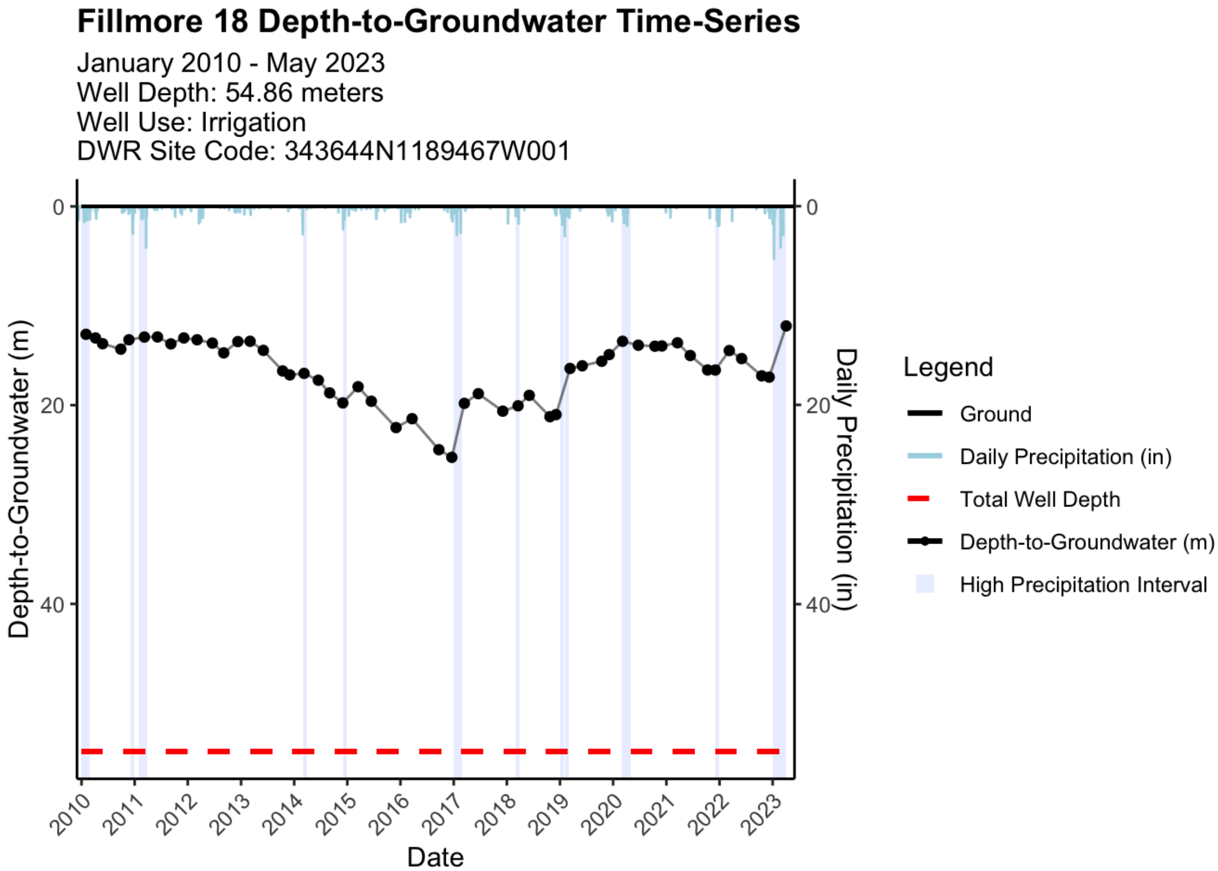
January 2010 - May 2023
Well Depth: 16.26 meters
Well Use: Residential
DWR Site Code: 344069N1189490W001



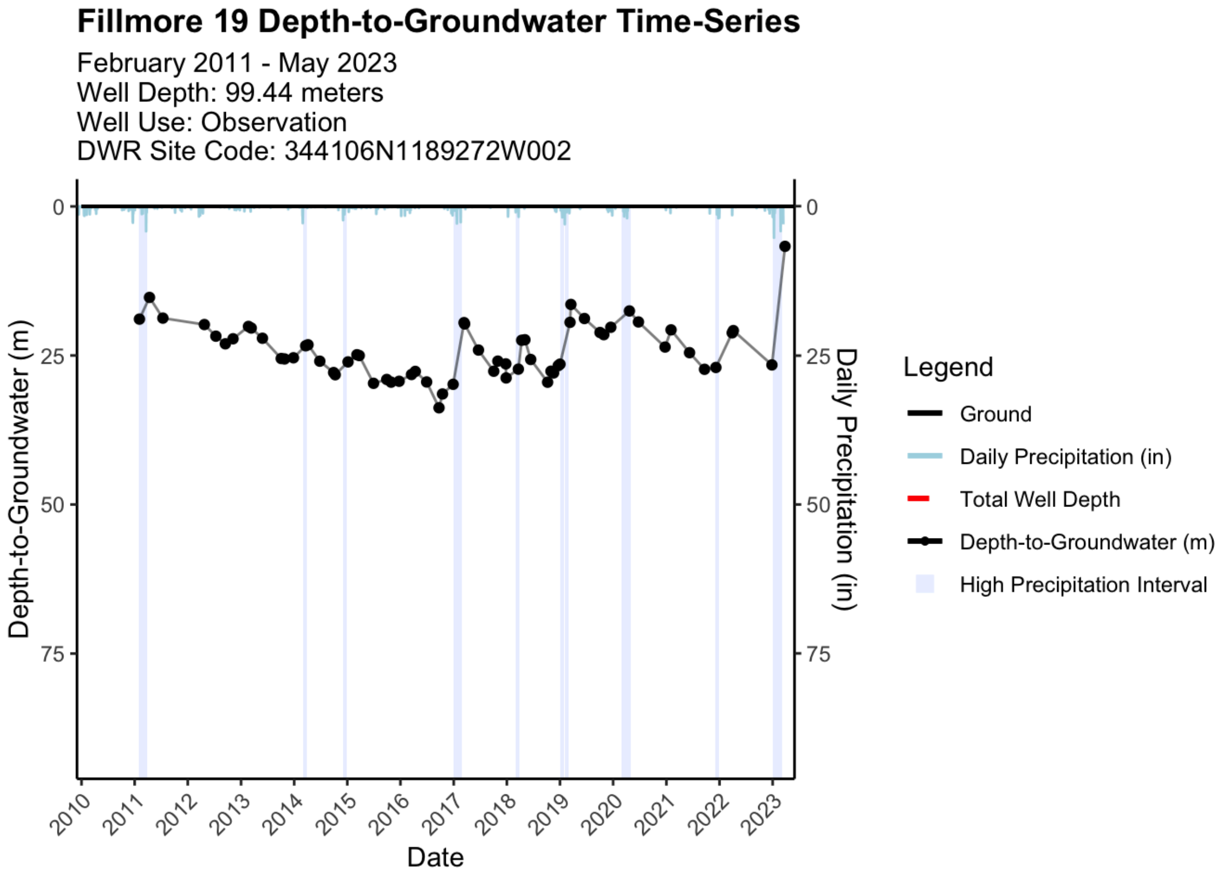
Fillmore 17 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: 220.68 meters
Max Recorded DTG: 62.24 meters
Well Use: Irrigation
DWR Site Code: 343900N1189831W001



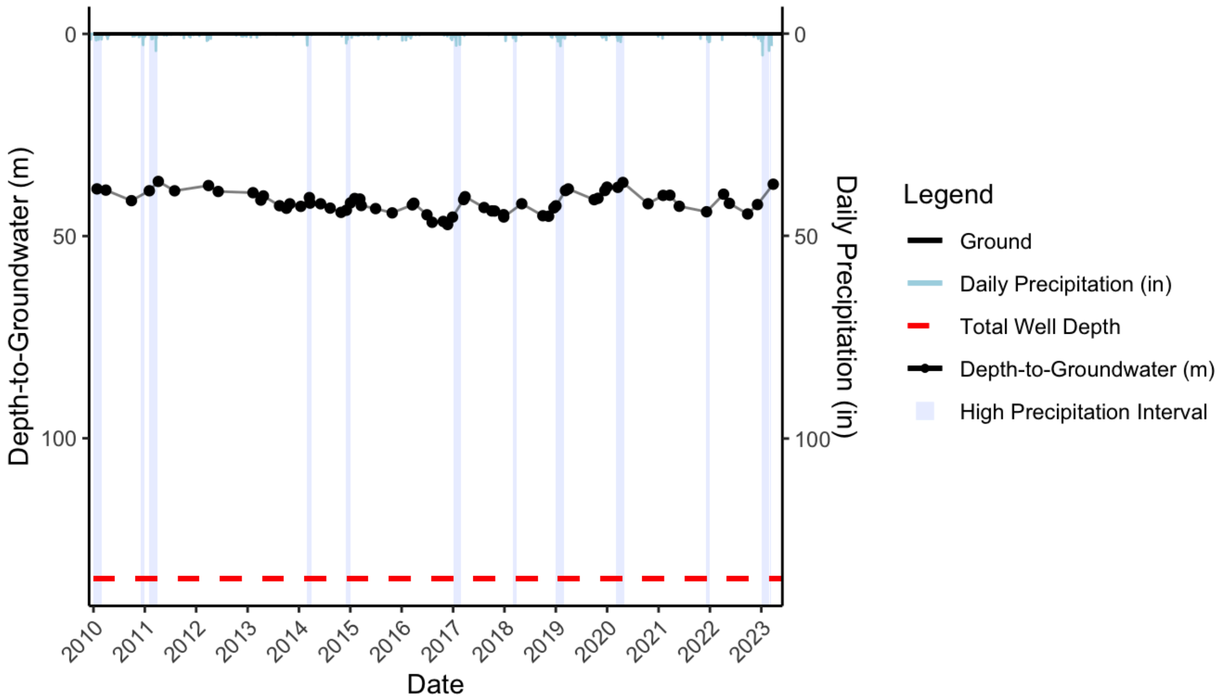


Fillmore 18 Depth-to-Groundwater Time-Series
January 2010 - May 2023
Well Depth: 54.86 meters
Well Use: Irrigation
DWR Site Code: 343644N1189467W001
Depth-to-Groundwater (m)
Daily Precipitation (in)
0
20
40
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Date
Legend
Ground
Daily Precipitation (in)
Total Well Depth
Depth-to-Groundwater (m)
High Precipitation Interval


Fillmore 19 Depth-to-Groundwater Time-Series
February 2011 - May 2023
Well Depth: 99.44 meters
Well Use: Observation
DWR Site Code: 344106N1189272W002
Depth-to-Groundwater (m)
Daily Precipitation (in)
0
25
50
75
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Date
Legend
Ground
Daily Precipitation (in)
Total Well Depth
Depth-to-Groundwater (m)
High Precipitation Interval

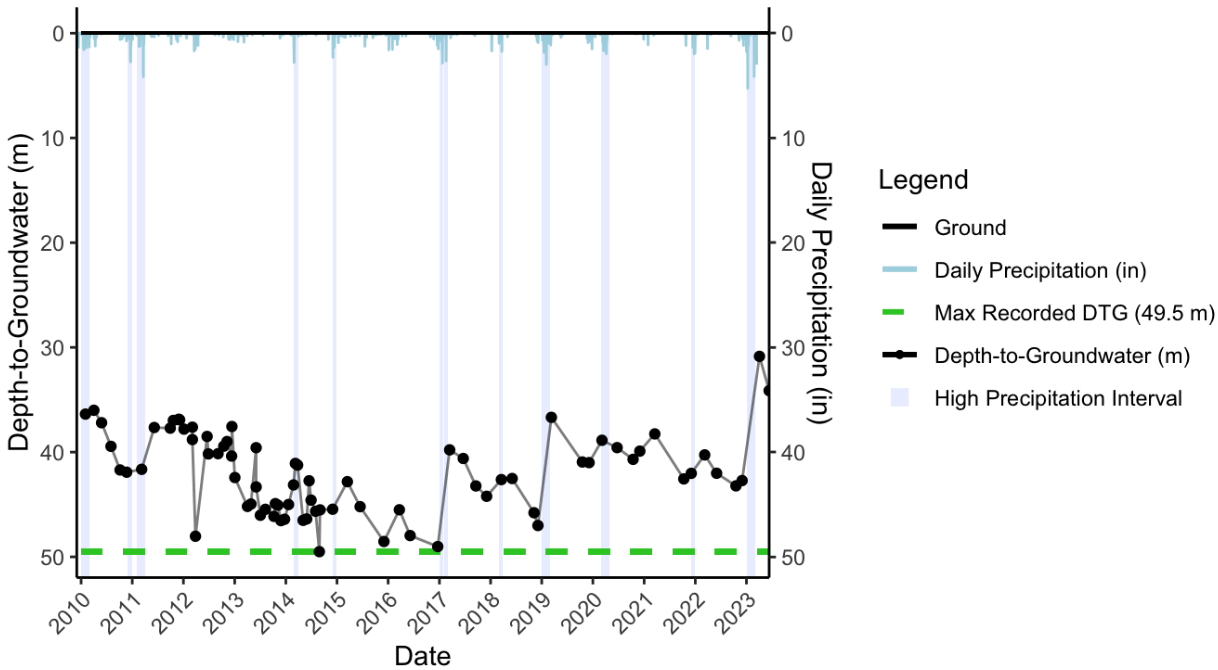
Fillmore 20 Depth-to-Groundwater Time-Series

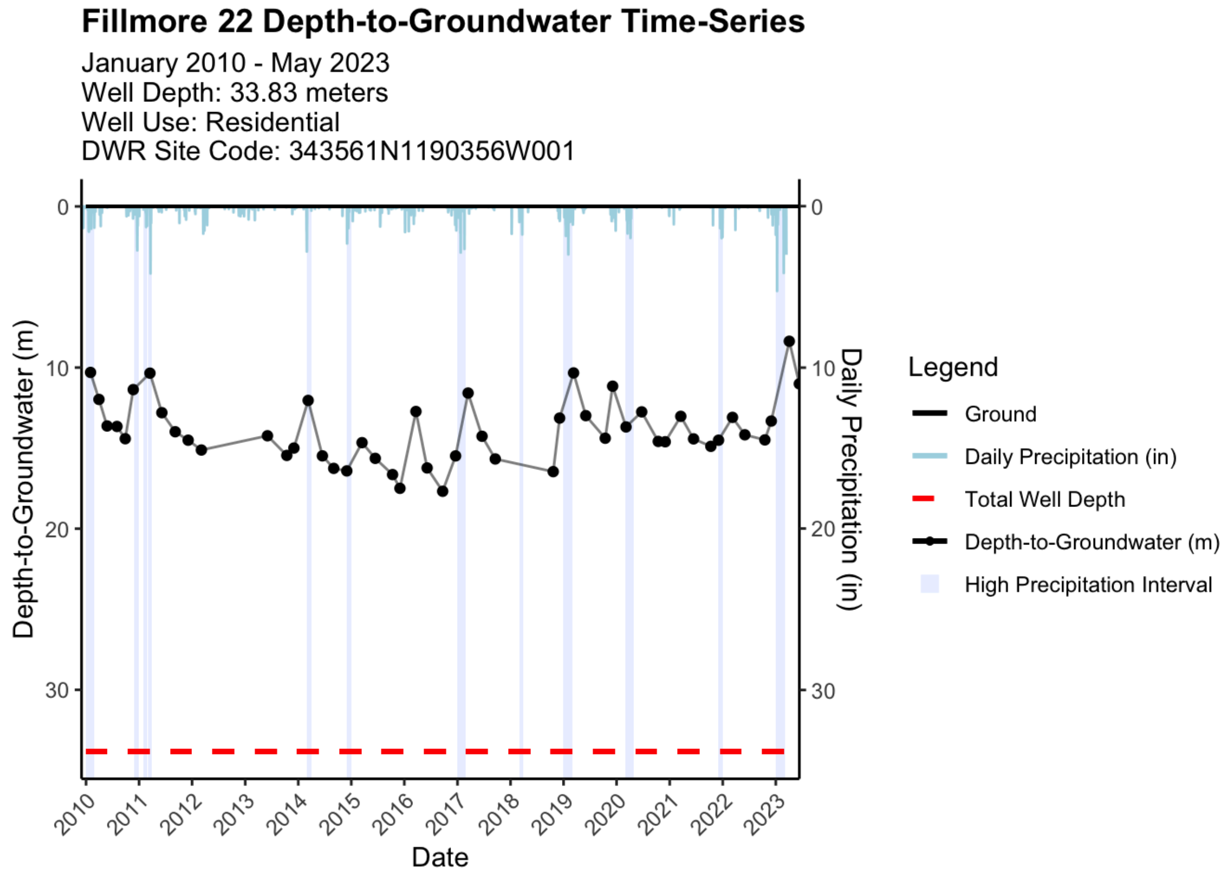
January 2010 - May 2023
Well Depth: 134.72 meters
Well Use: Unknown
DWR Site Code: 343763N1190076W001



Fillmore 21 Depth-to-Groundwater Time-Series

January 2010 - May 2023
Well Depth: 172.82 meters
Max Recorded DTG: 49.5 meters
Well Use: Irrigation
DWR Site Code: 344106N1189431W001



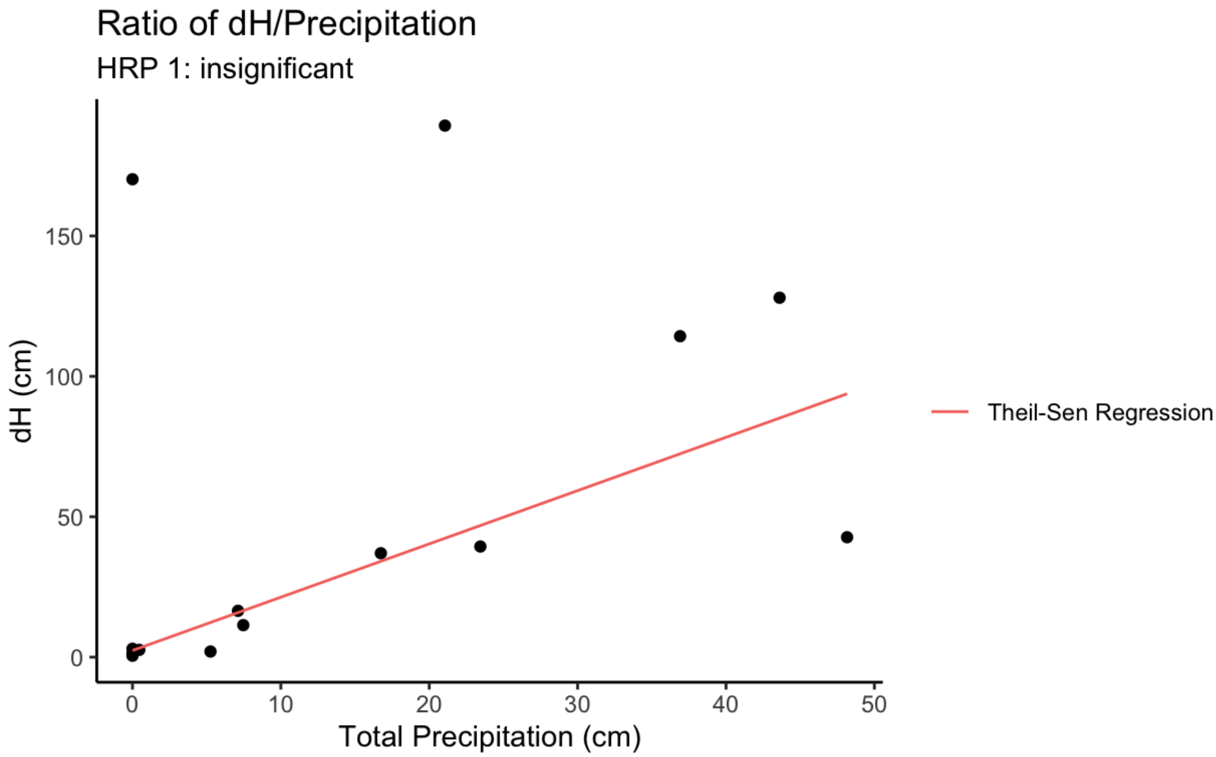


3.2.2 Water-Level Rise Regressions

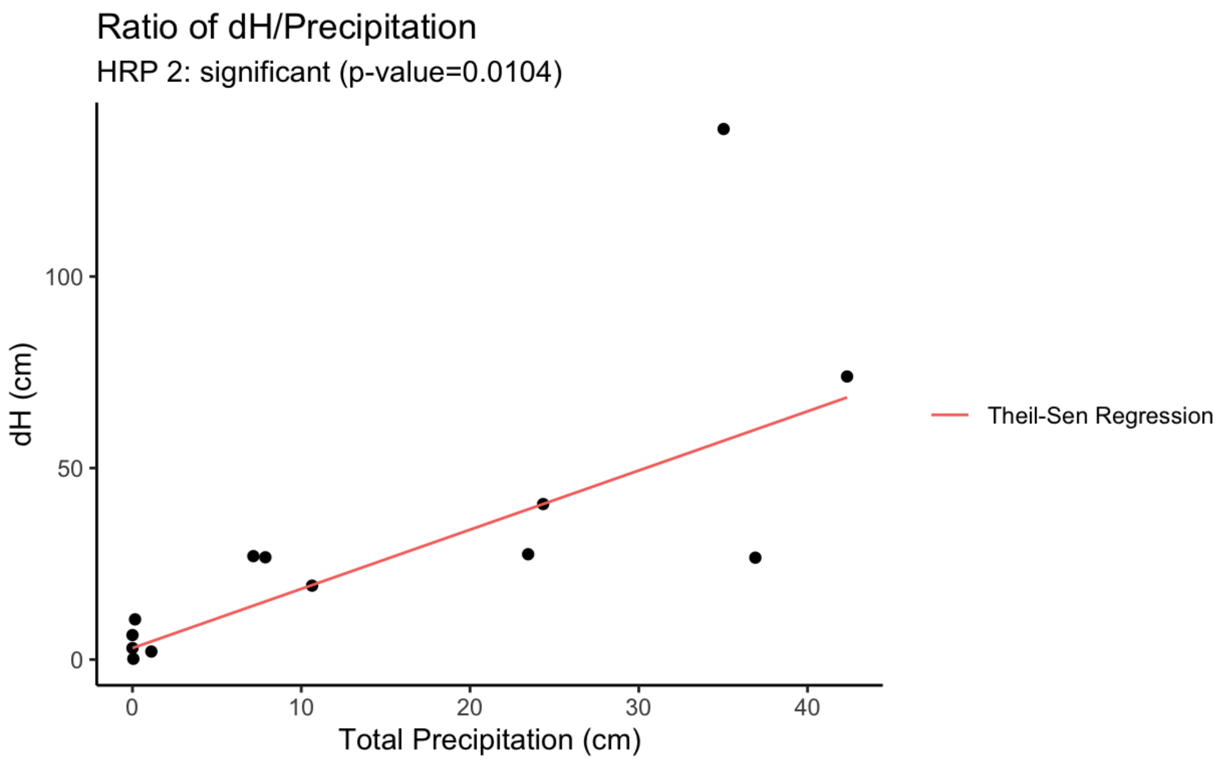
A. East Grove Shallow Groundwater Monitoring Wells

For all plots and regressions below, water-level rise (delta-H) is assumed to be a linear function of precipitation. The slope equals the average ratio between delta-H and total precipitation during the same time interval. None of the intercepts calculated in the models were significant.

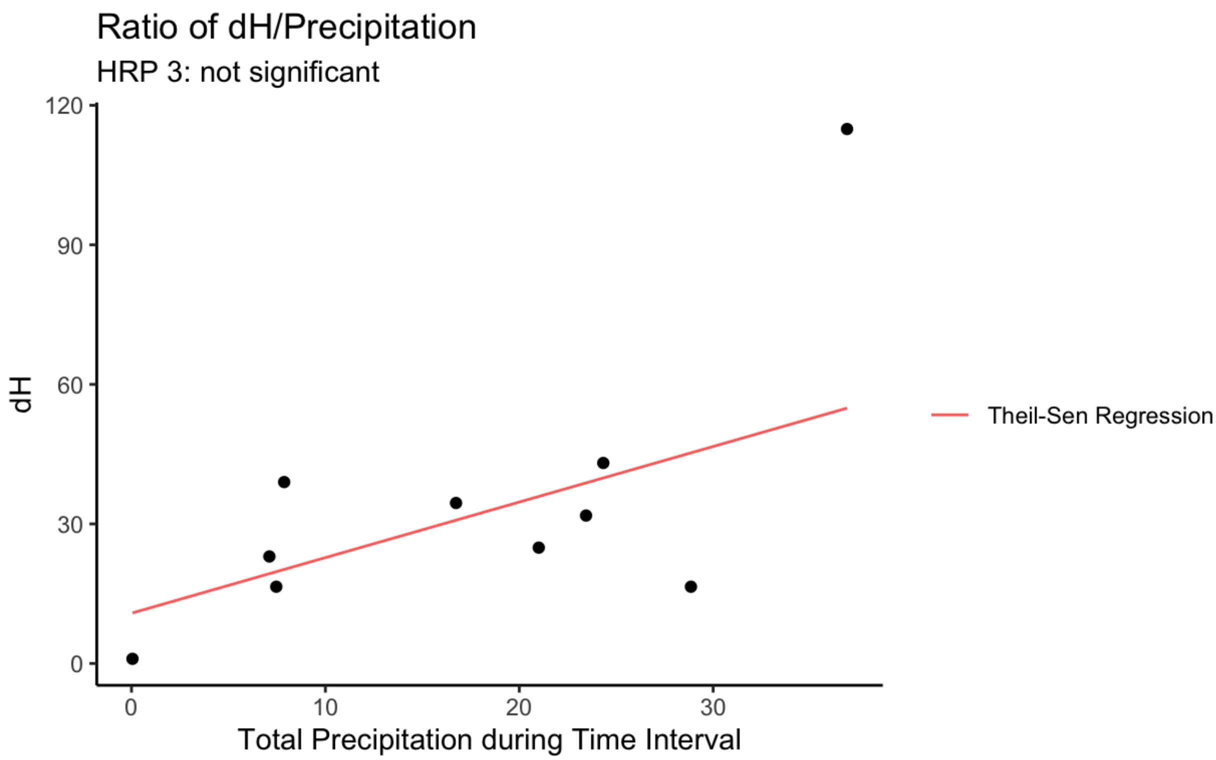
Hedrick Ranch Preserve



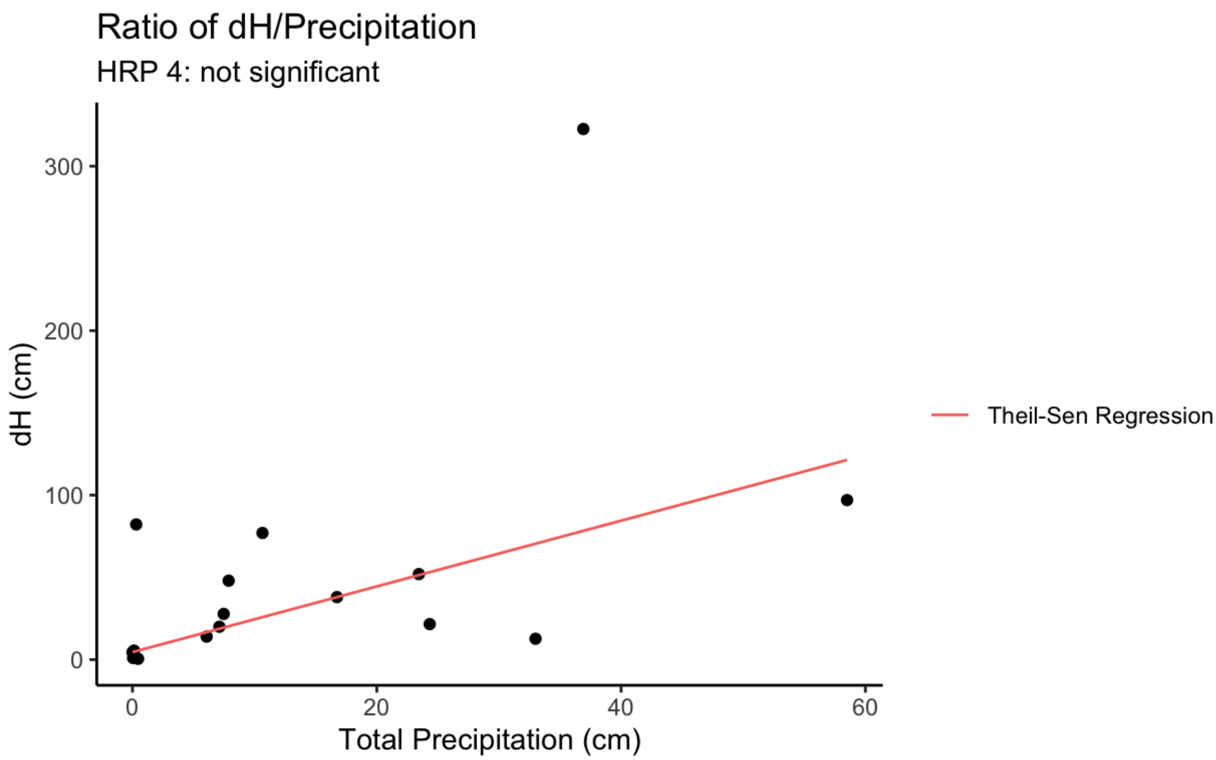
	Estimate	t-value	p-value
Mean dH/precipitation	1.898	1.718	0.111



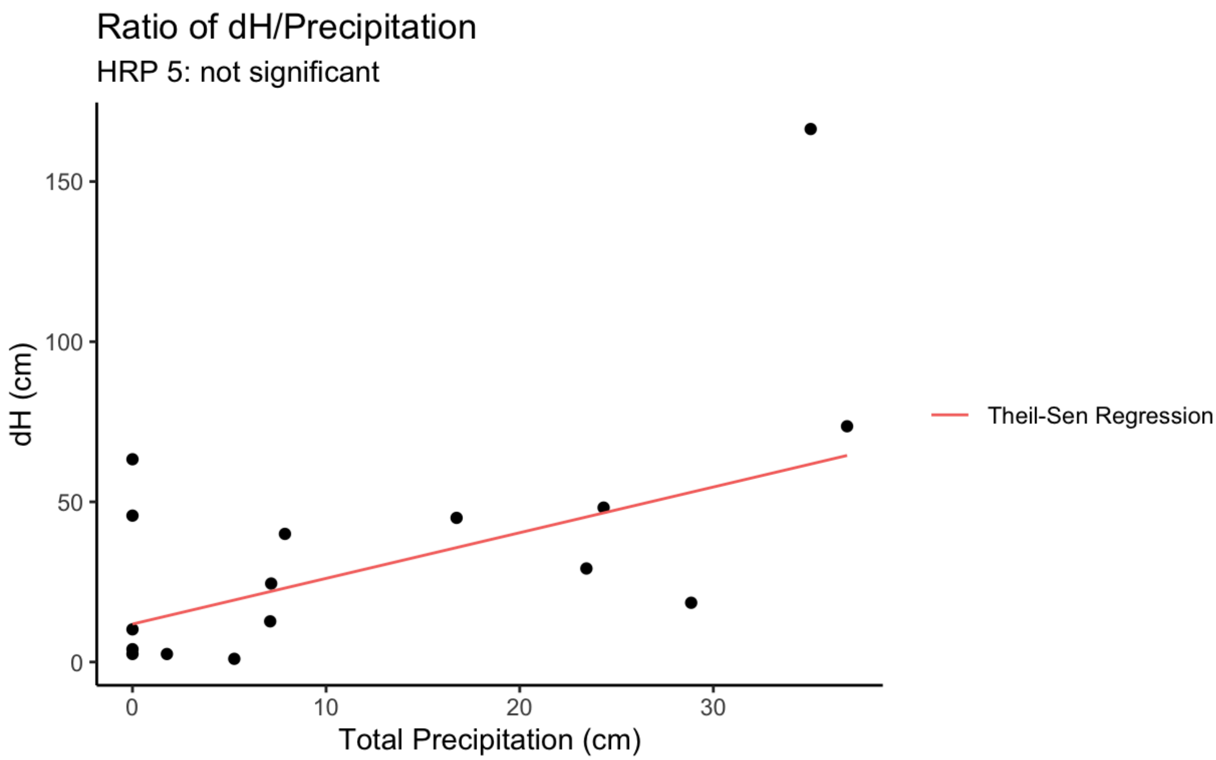
	Estimate	t-value	p-value
Mean dH/precipitation	1.5452	3.085	0.0104



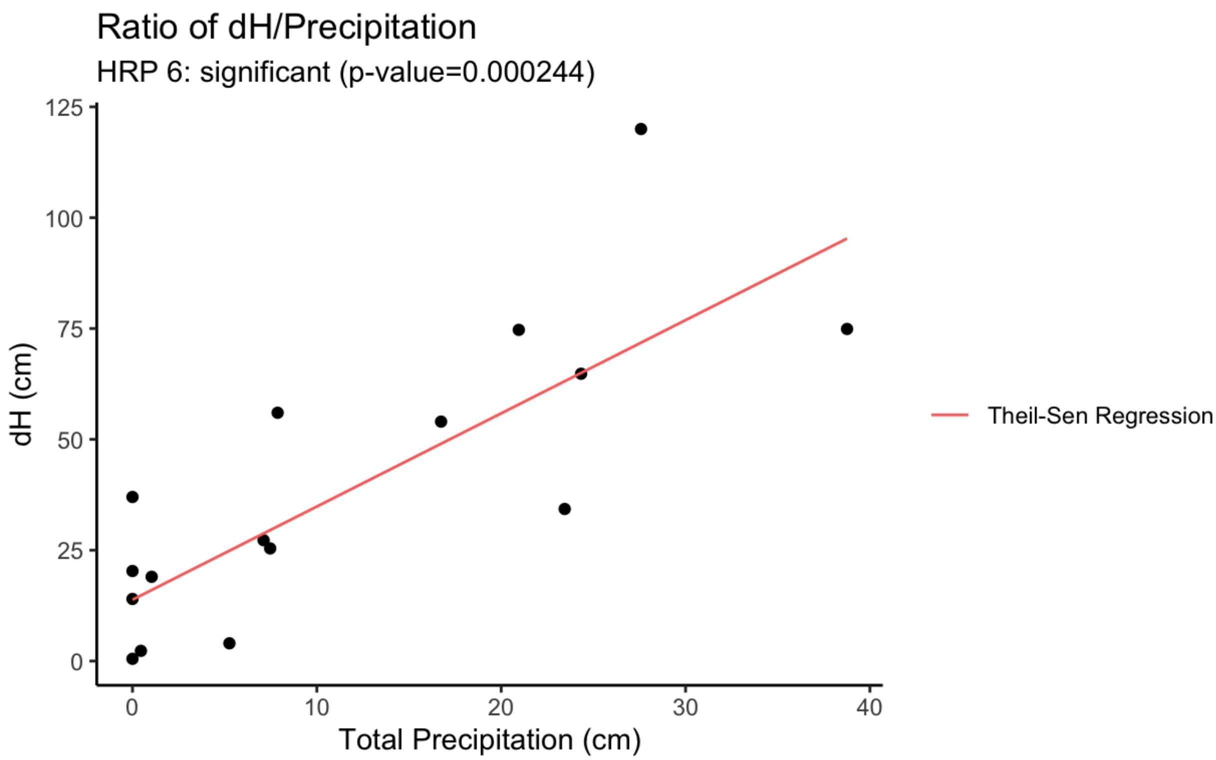
	Estimate	t-value	p-value
Mean dH/precipitation	1.1946	1.643	0.139



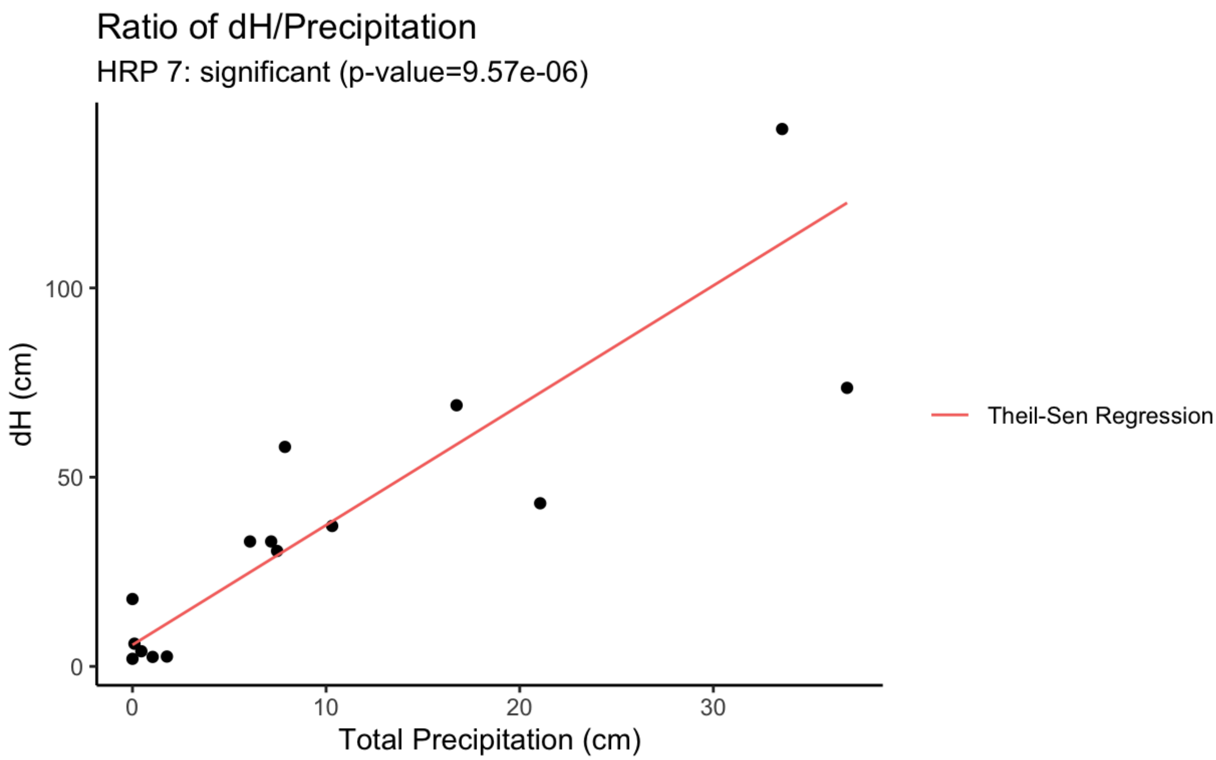
	Estimate	t-value	p-value
Mean dH/precipitation	1.998	1.890	0.0783



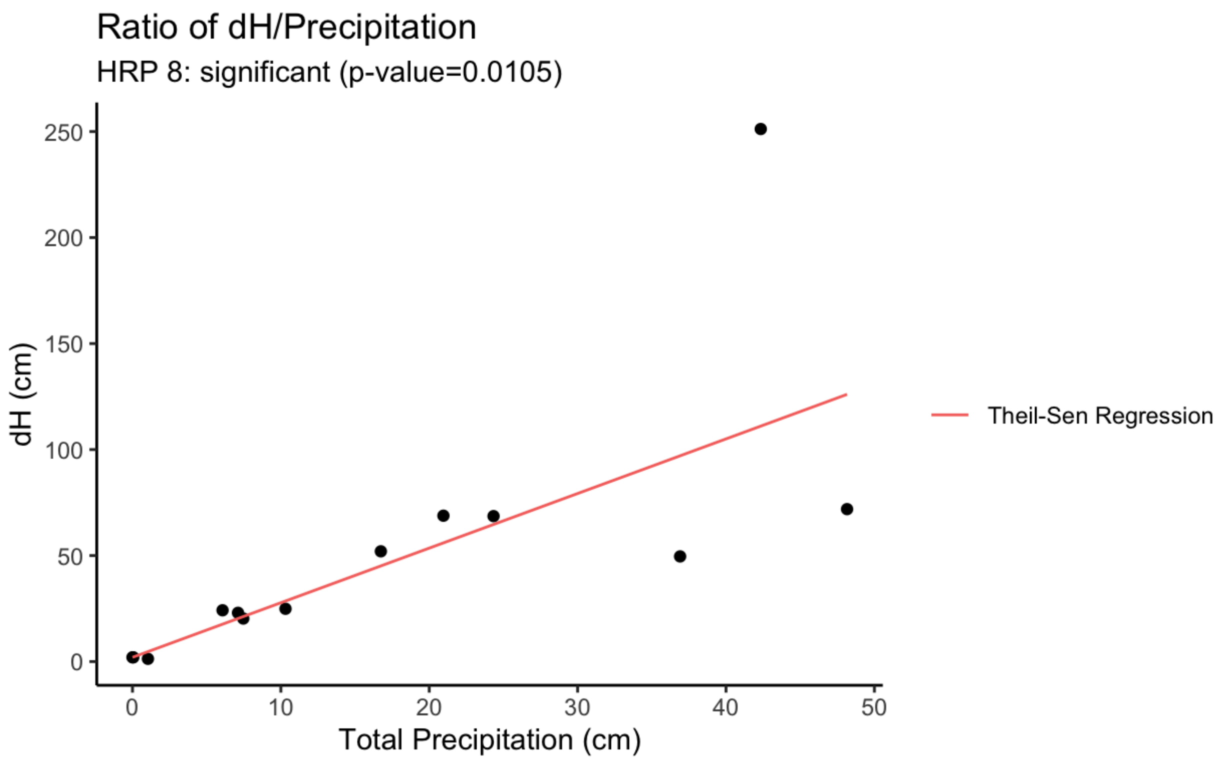
	Estimate	t-value	p-value
Mean dH/precipitation	1.426	2.094	0.0549



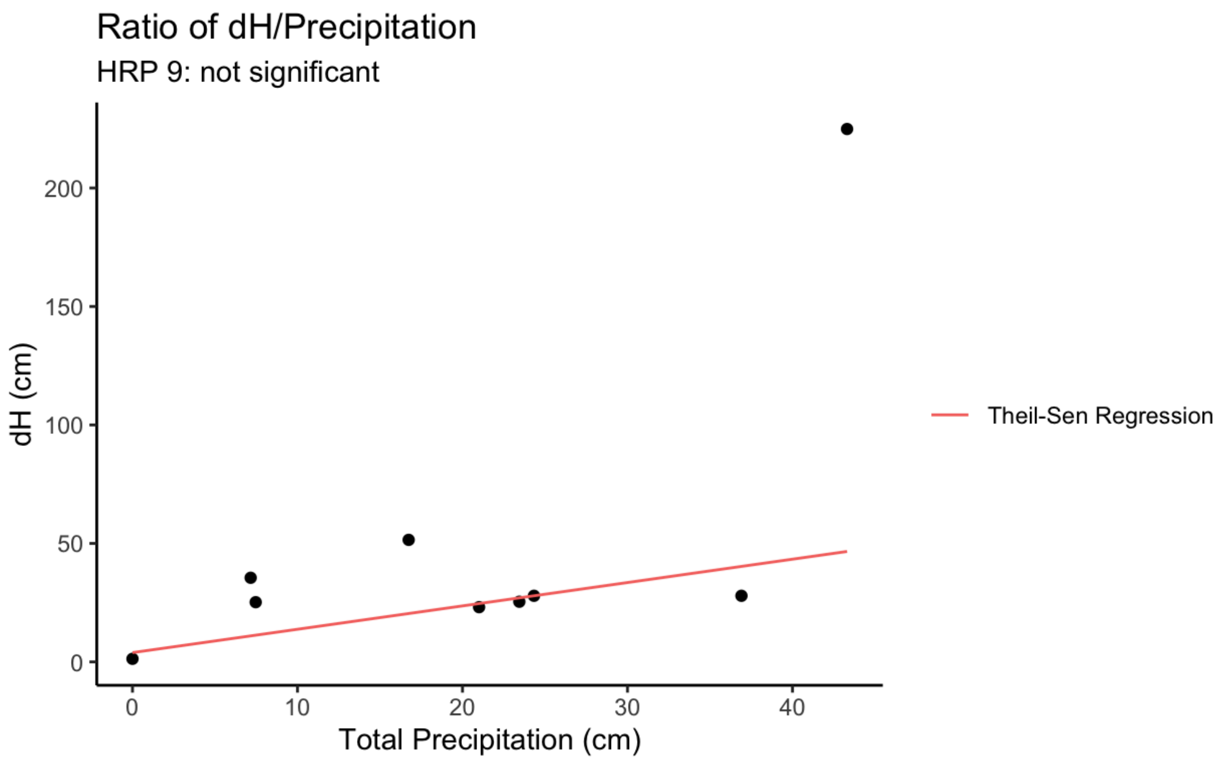
	Estimate	t-value	p-value
Mean dH/precipitation	2.1020	4.878	0.000244



	Estimate	t-value	p-value
Mean dH/precipitation	3.1650	6.984	9.57e-06

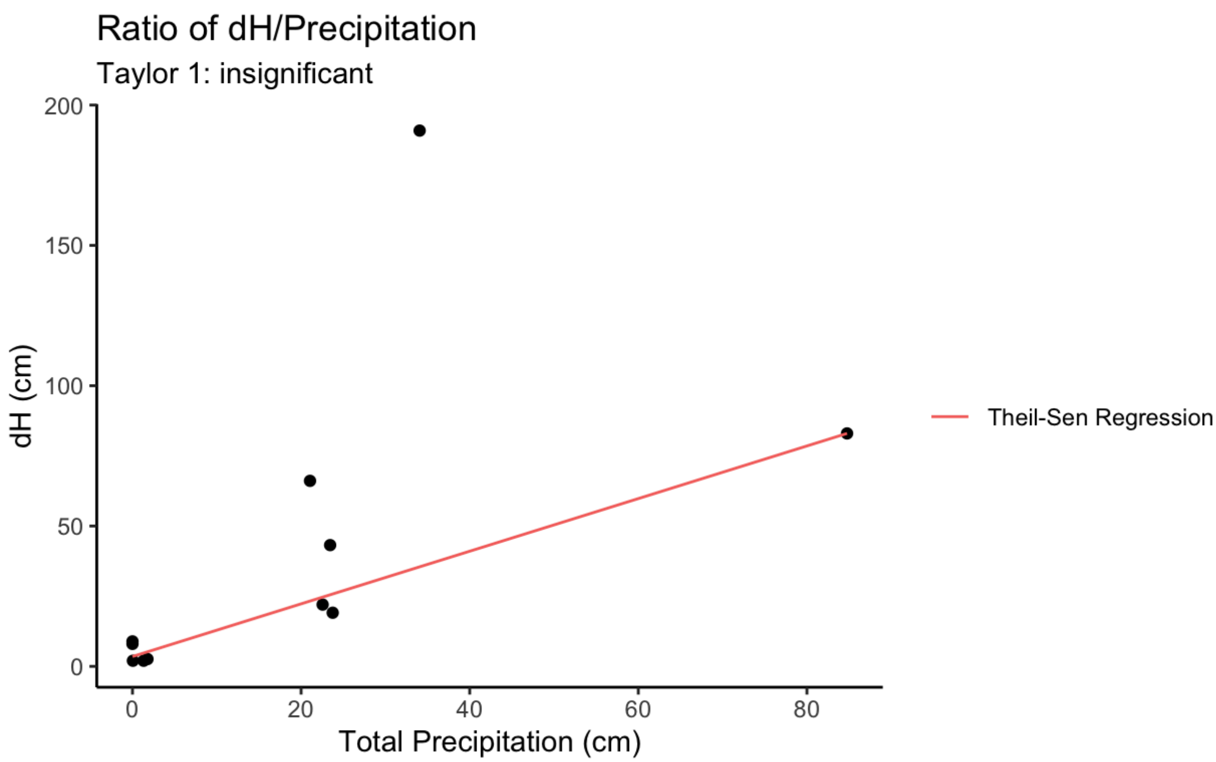


	Estimate	t-value	p-value
Mean dH/precipitation	2.5757	3.078	0.0105

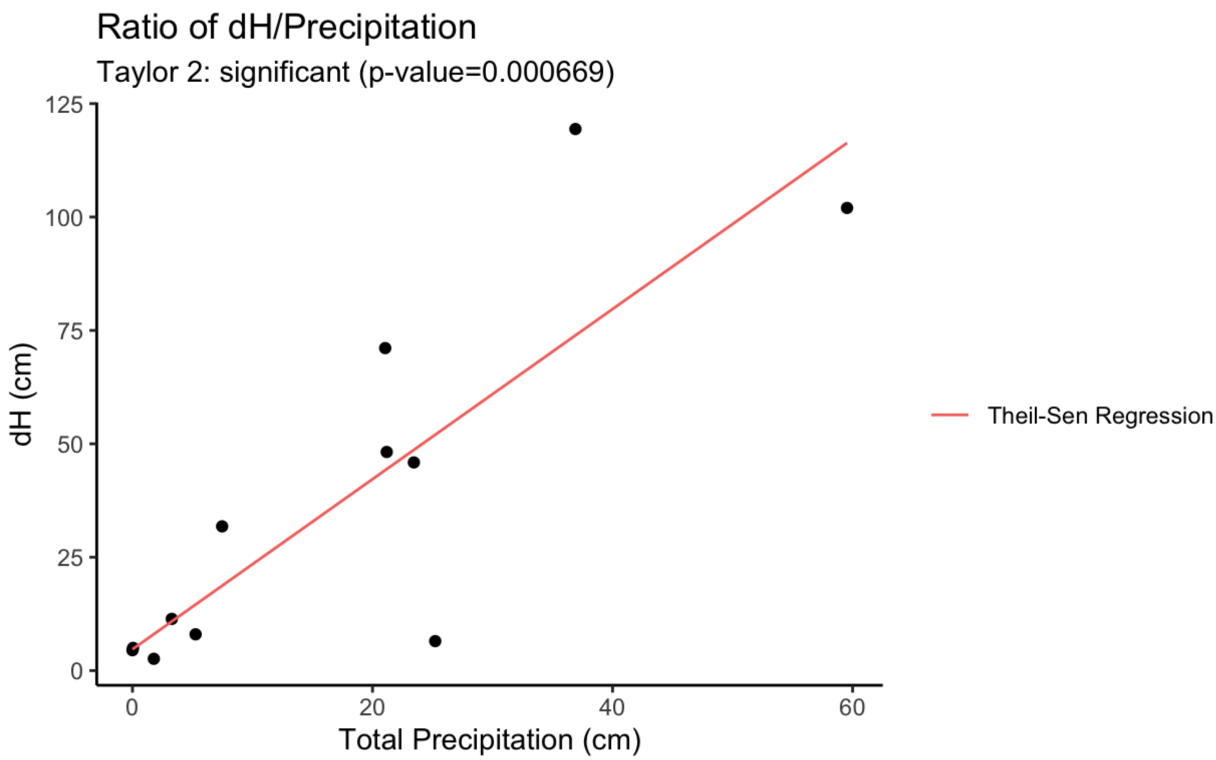


	Estimate	t-value	p-value
Mean dH/precipitation	0.9856	1.7388	0.589

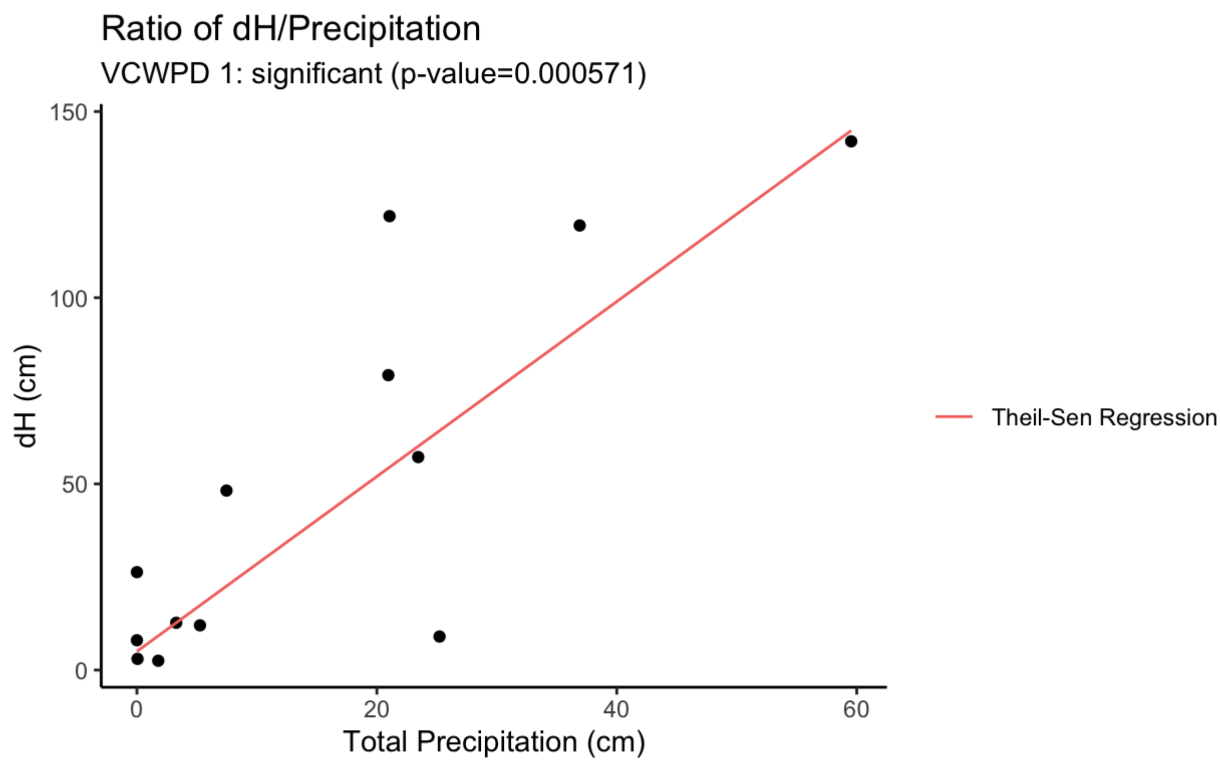
Taylor Ranch



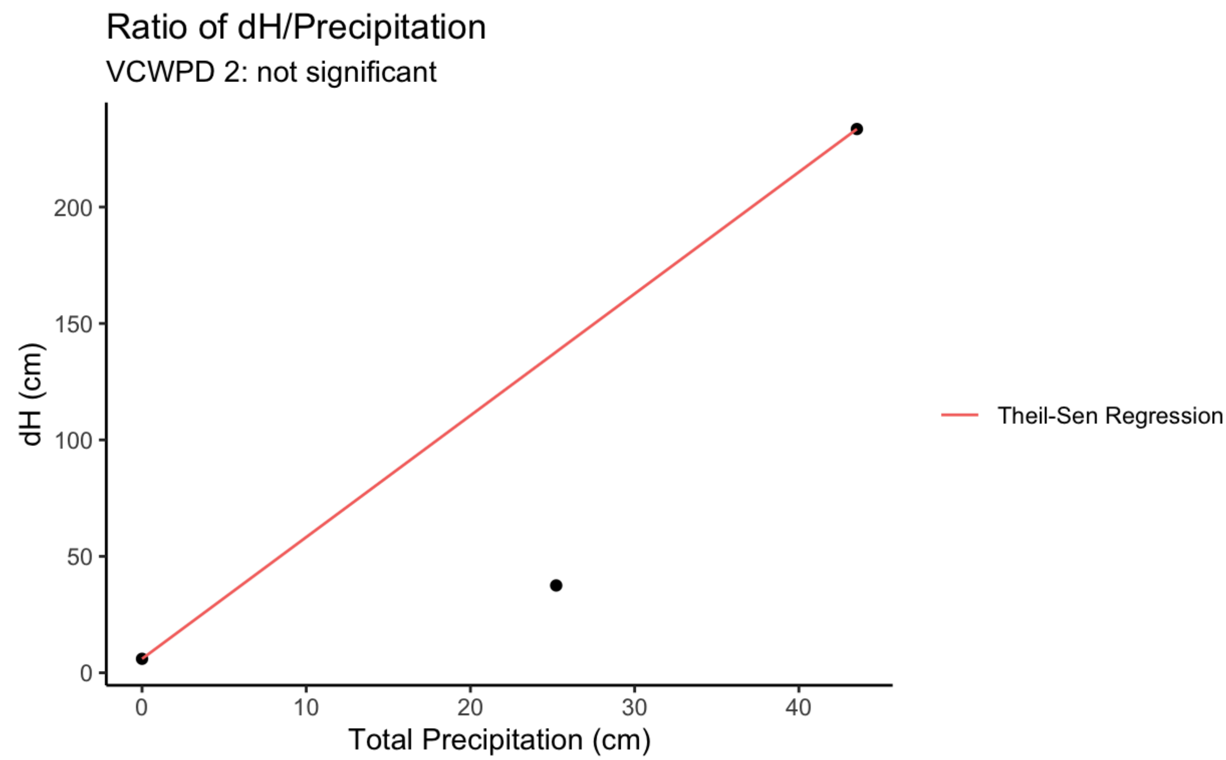
	Estimate	t-value	p-value
Mean dH/precipitation	0.9378	1.374	0.203



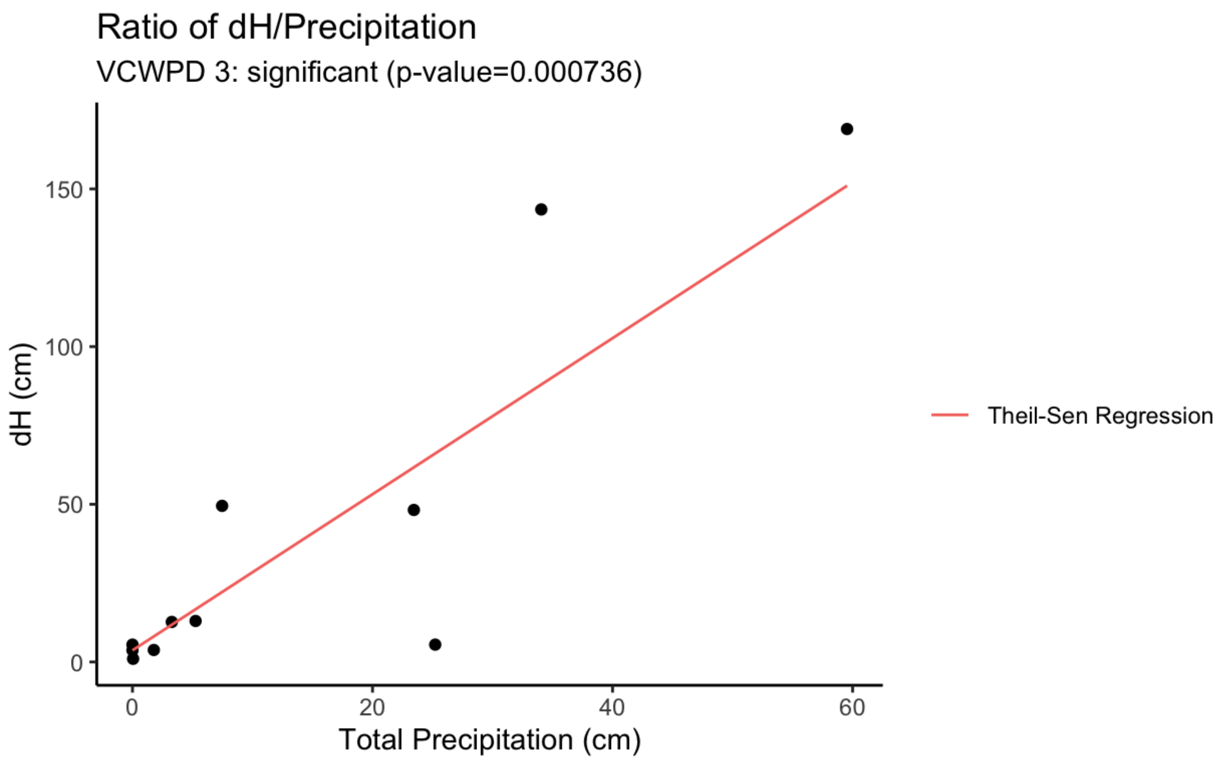
	Estimate	t-value	p-value
Mean dH/precipitation	1.8749	4.852	0.000669



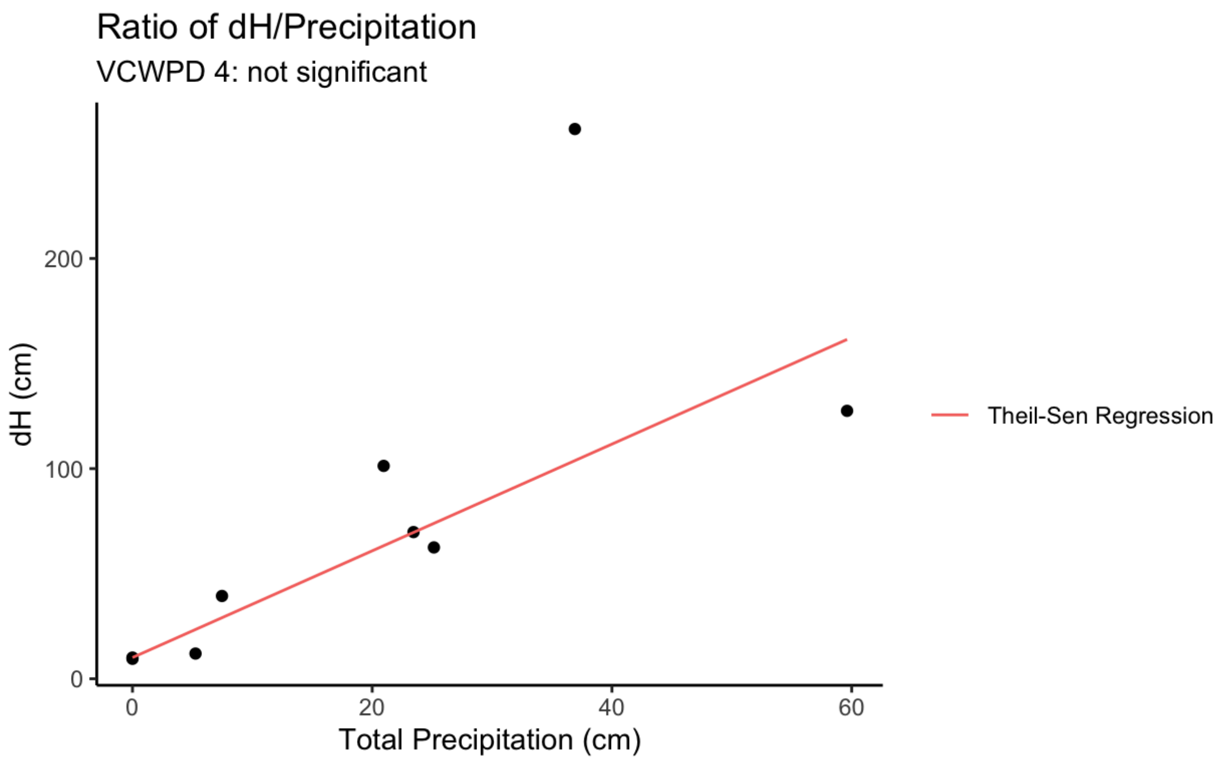
	Estimate	t-value	p-value
Mean dH/precipitation	2.3495	4.781	0.000571



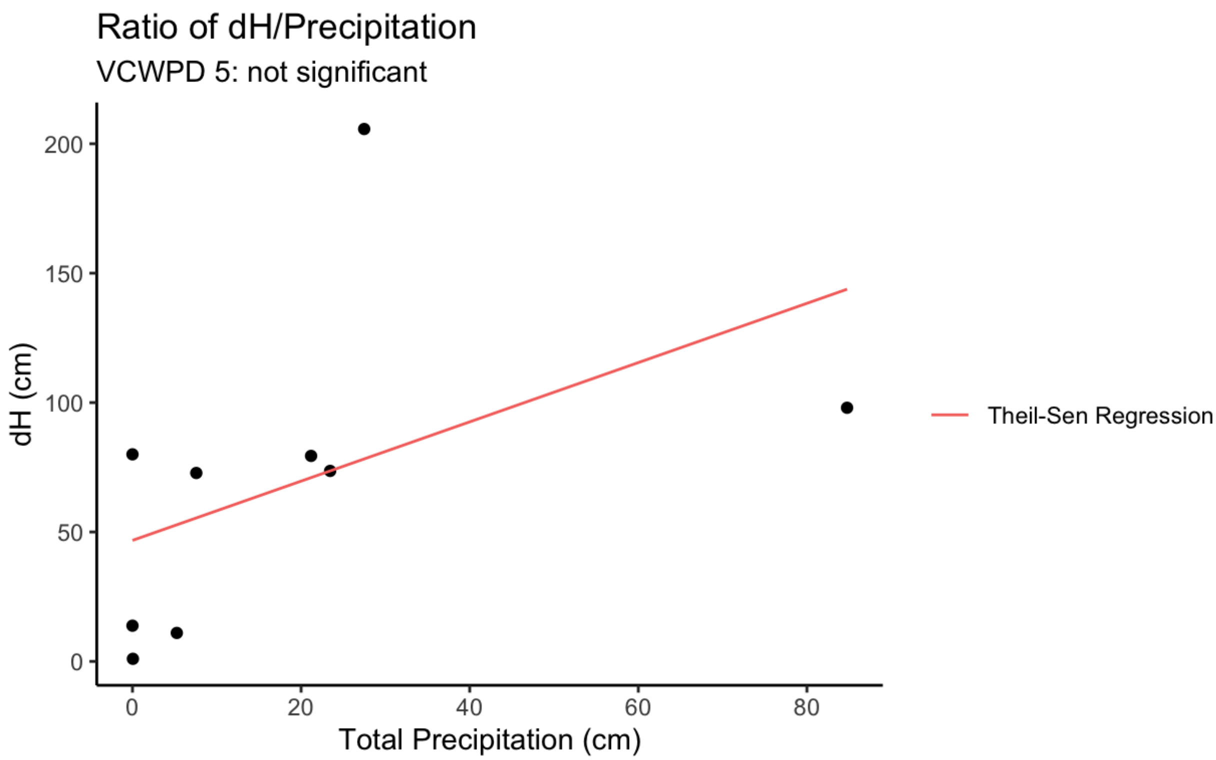
	Estimate	t-value	p-value
Mean dH/precipitation	5.226	1.611	0.354



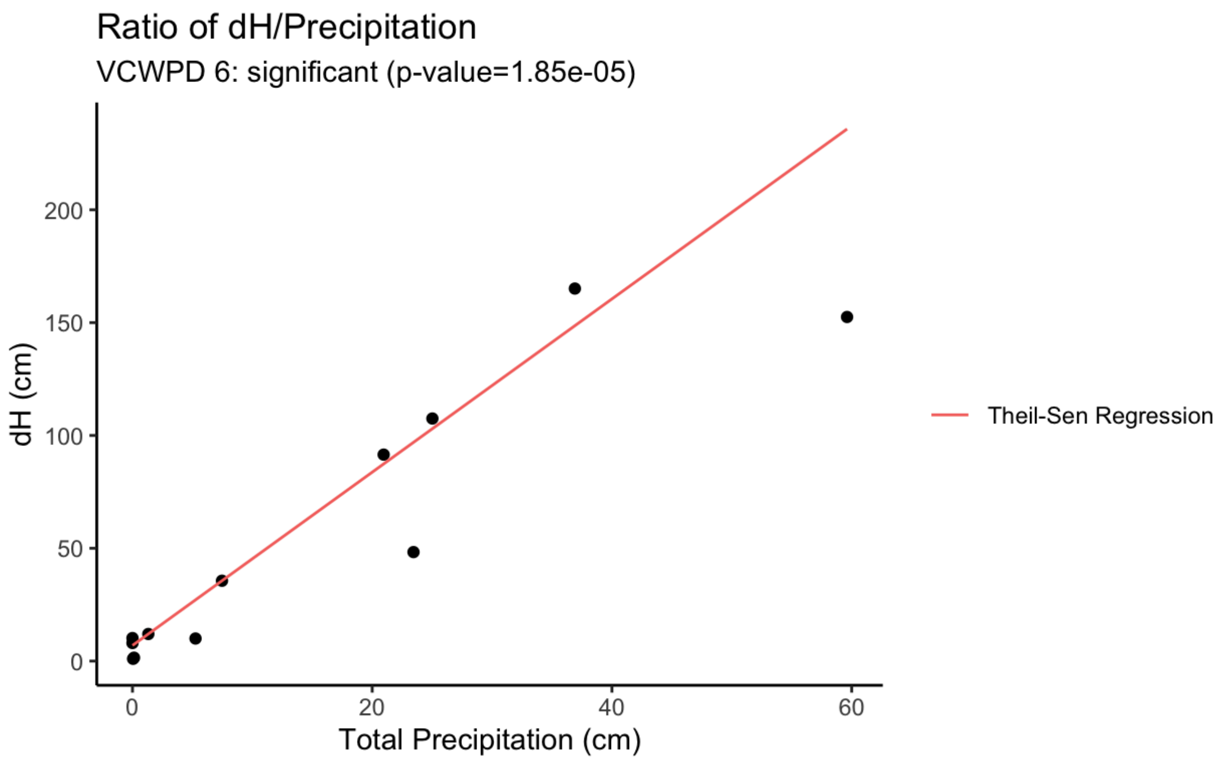
	Estimate	t-value	p-value
Mean dH/precipitation	2.4742	5.003	0.000736



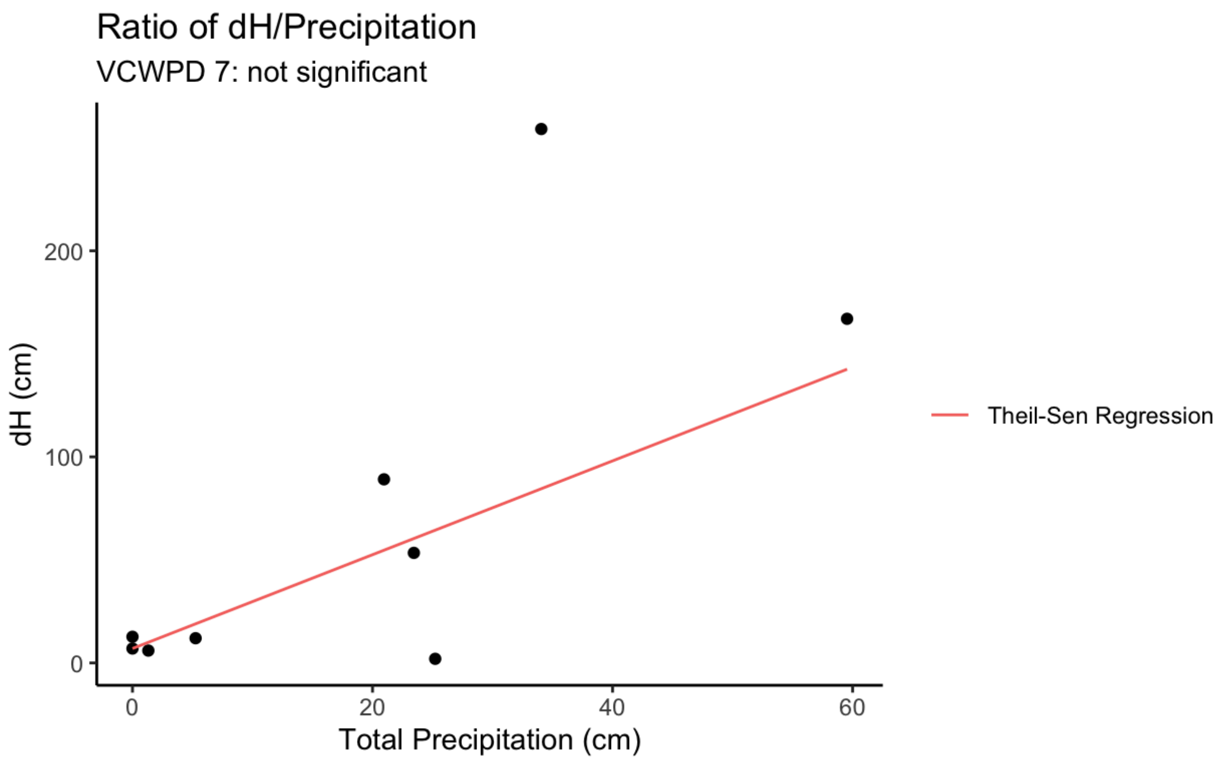
	Estimate	t-value	p-value
Mean dH/precipitation	2.539	2.229	0.061



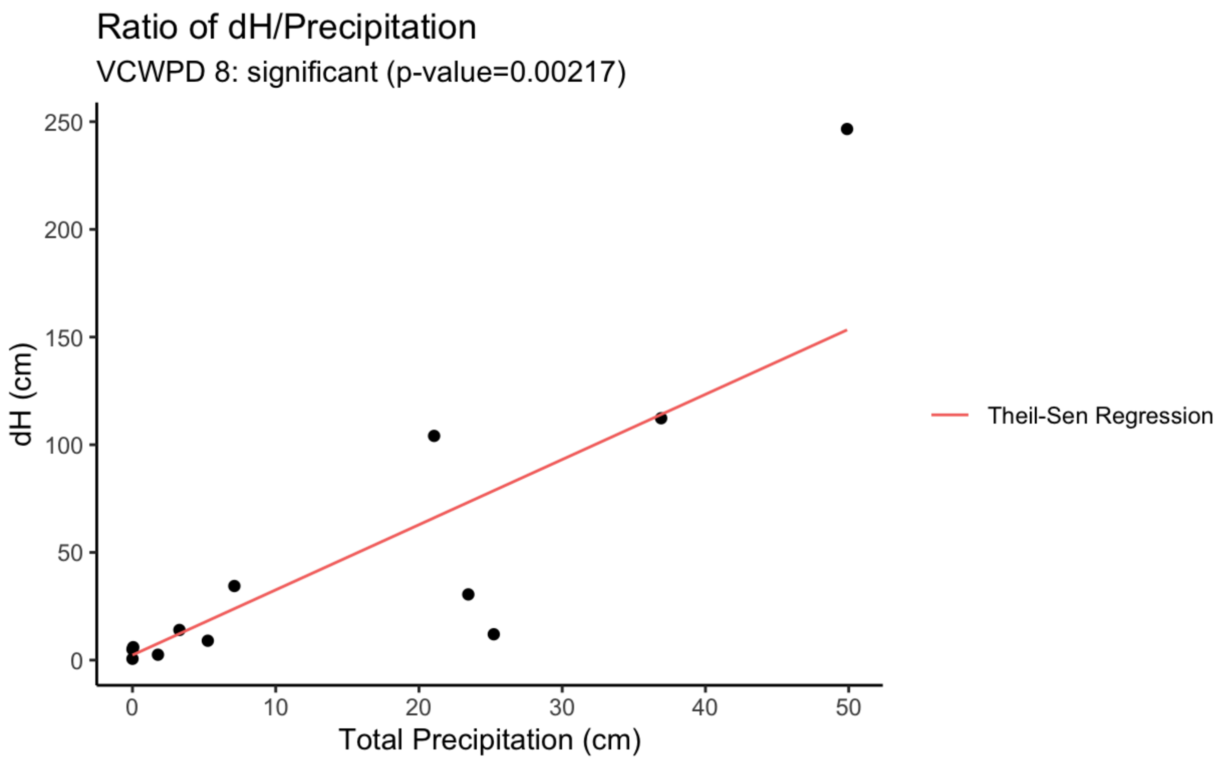
	Estimate	t-value	p-value
Mean dH/precipitation	1.1451	1.469	0.185



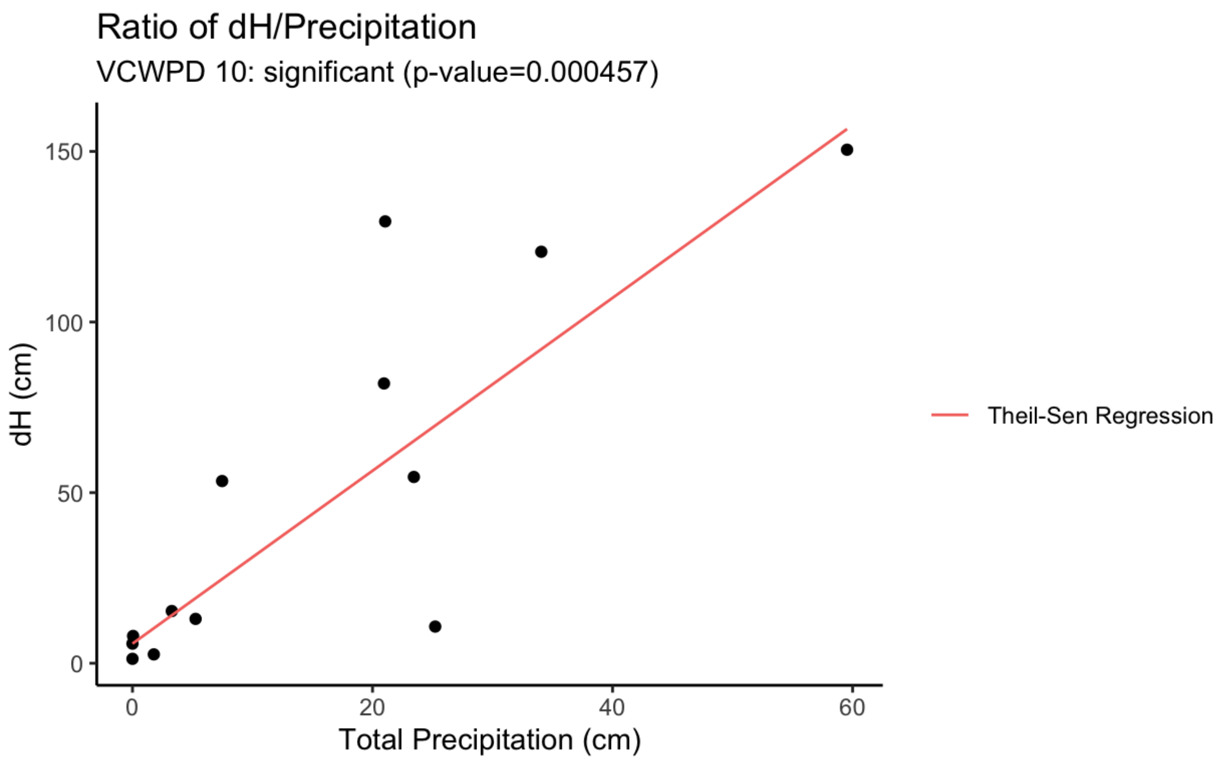
	Estimate	t-value	p-value
Mean dH/precipitation	3.8394	7.596	1.85e-05



	Estimate	t-value	p-value
Mean dH/precipitation	2.276	1.776	0.119



	Estimate	t-value	p-value
Mean dH/precipitation	3.0266	4.093	0.00217

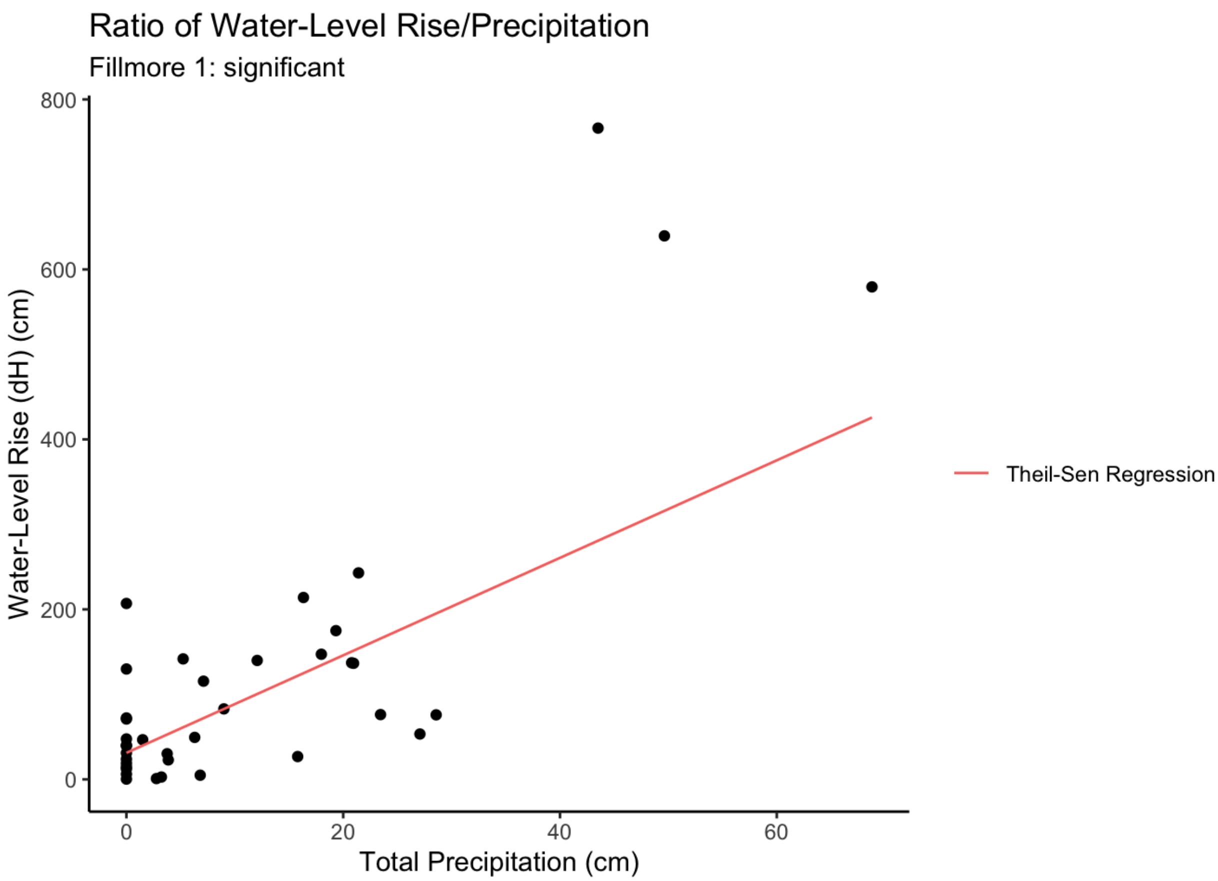


	Estimate	t-value	p-value
Mean dH/precipitation	2.5332	4.920	0.00457

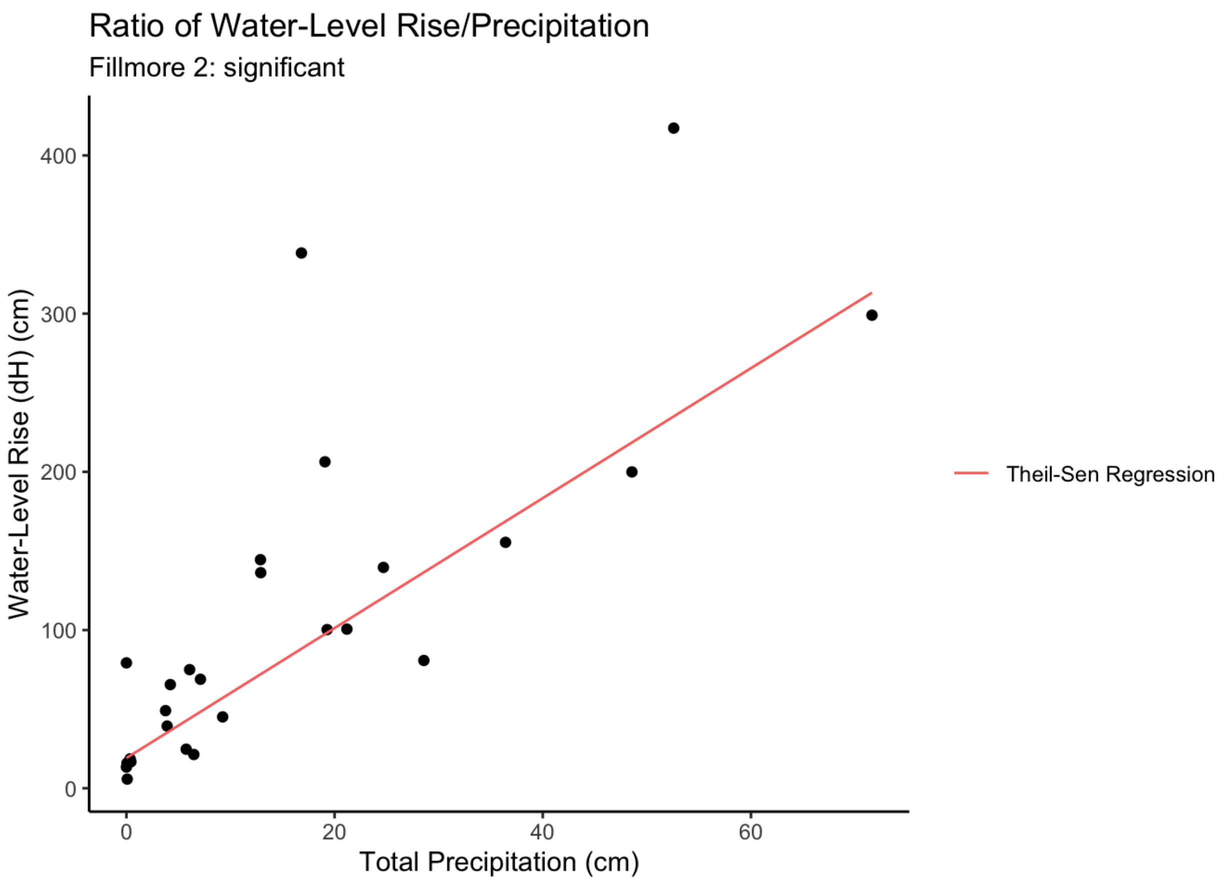
Theil-Sen Recharge Ratio for All Wells

well_id	ratio_slope	ratio_p
Taylor 1	0.9377919	0.2028359
Taylor 2	1.8749496	0.0006692
HRP 1	1.8982002	0.1114607
HRP 2	1.5452139	0.0103854
HRP 3	1.1946066	0.1389085
HRP 4	1.9977991	0.0782885
HRP 5	1.4261560	0.0549272
HRP 6	2.1019682	0.0002441
HRP 7	3.1649513	0.0000096
HRP 8	2.5757482	0.0105026
HRP 9	0.9856071	0.5885335
VCWPD 1	2.3494600	0.0005708
VCWPD 2	5.2256085	0.3537372
VCWPD 3	2.4742100	0.0007363
VCWPD 4	2.5391941	0.0610234
VCWPD 5	1.1450967	0.1852553
VCWPD 6	3.8393961	0.0000185
VCWPD 7	2.2764263	0.1190017
VCWPD 8	3.0265917	0.0021702
VCWPD 10	2.5331707	0.0004571

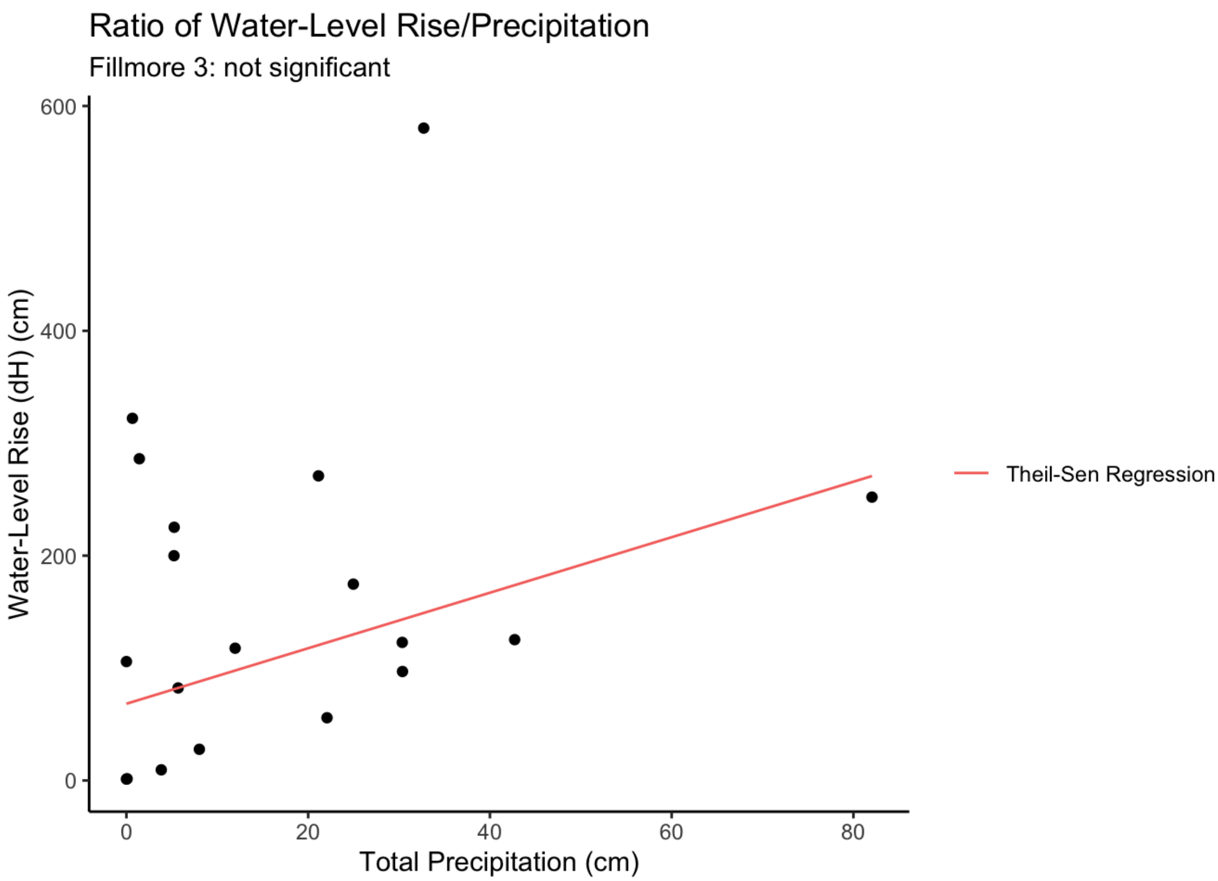
B. Fillmore Subbasin Wells



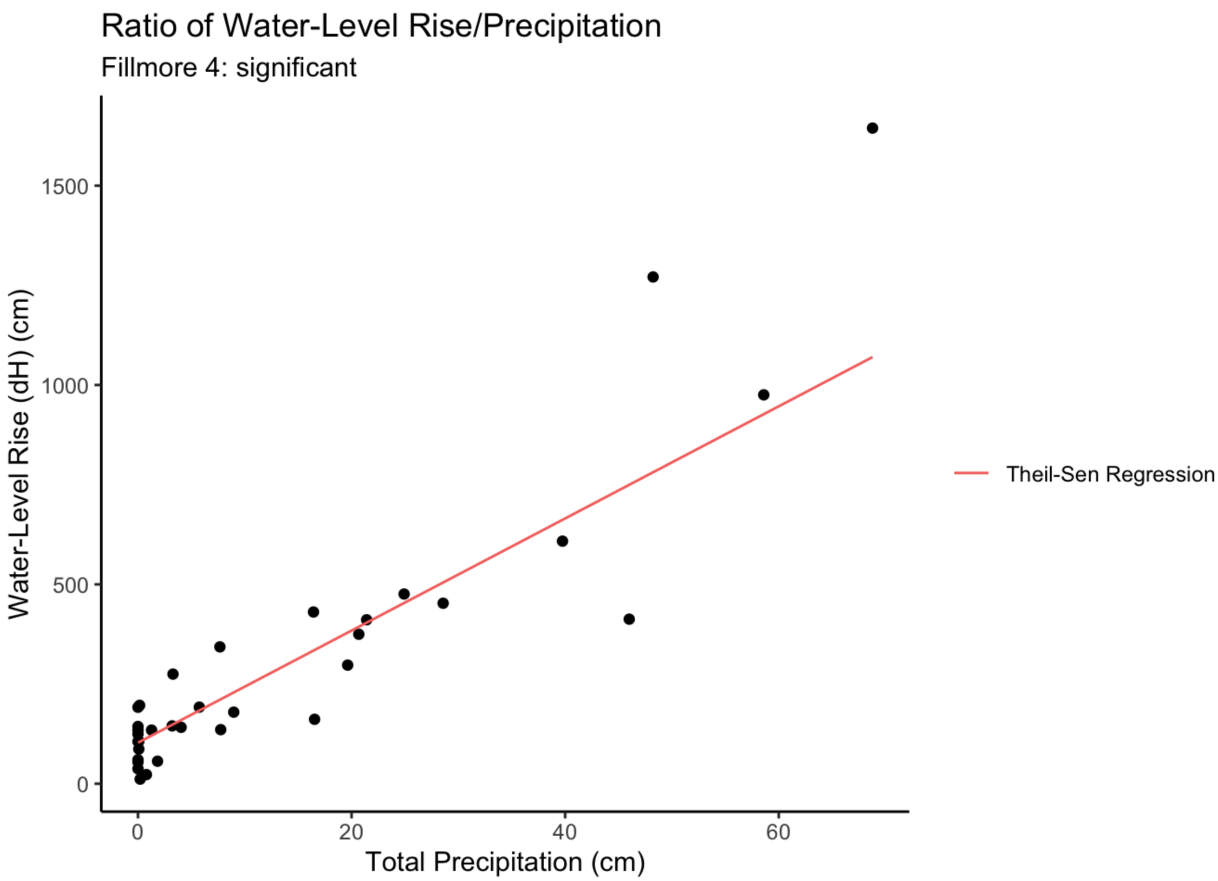
	Estimate	t-value	p-value
Mean dH/precipitation	5.736	4.676	0.0000403



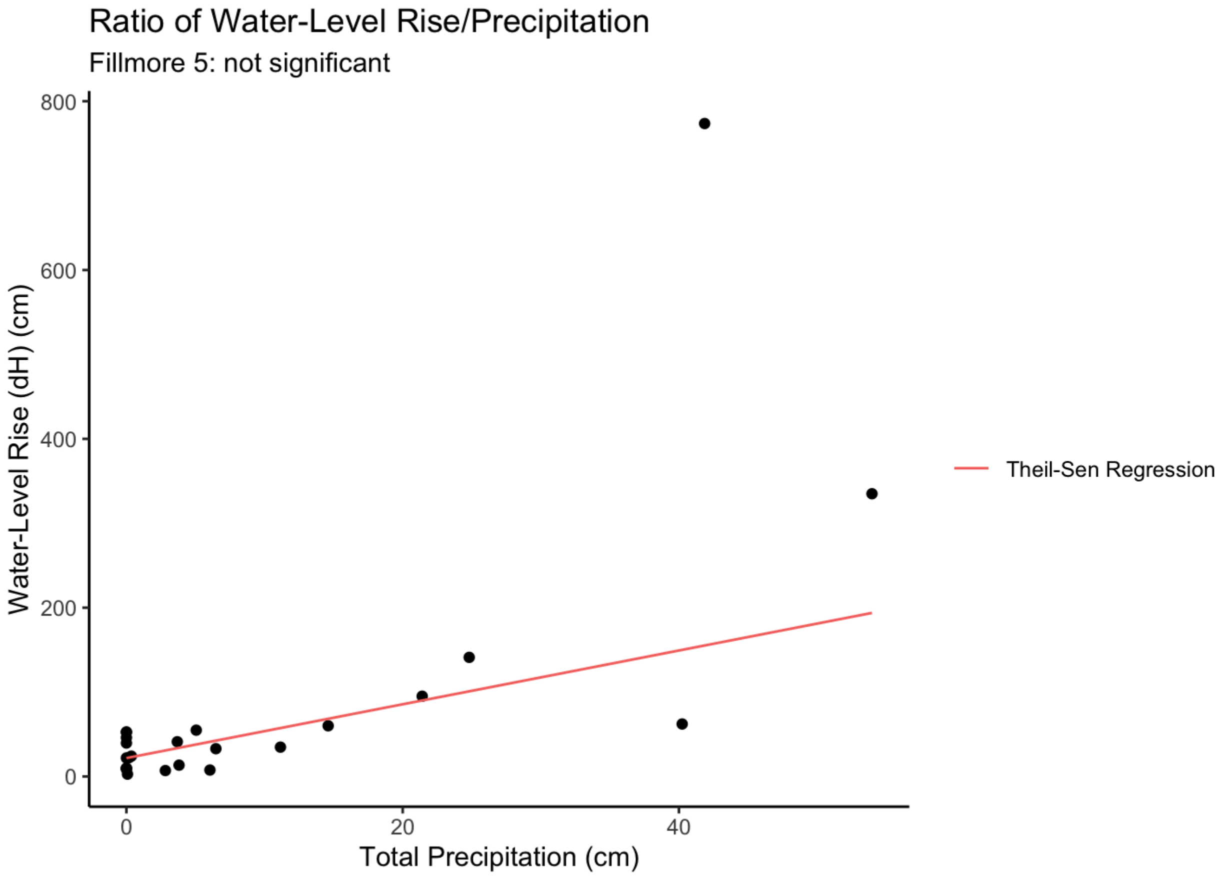
	Estimate	t-value	p-value
Mean dH/precipitation	4.1065	5.193	0.0000255



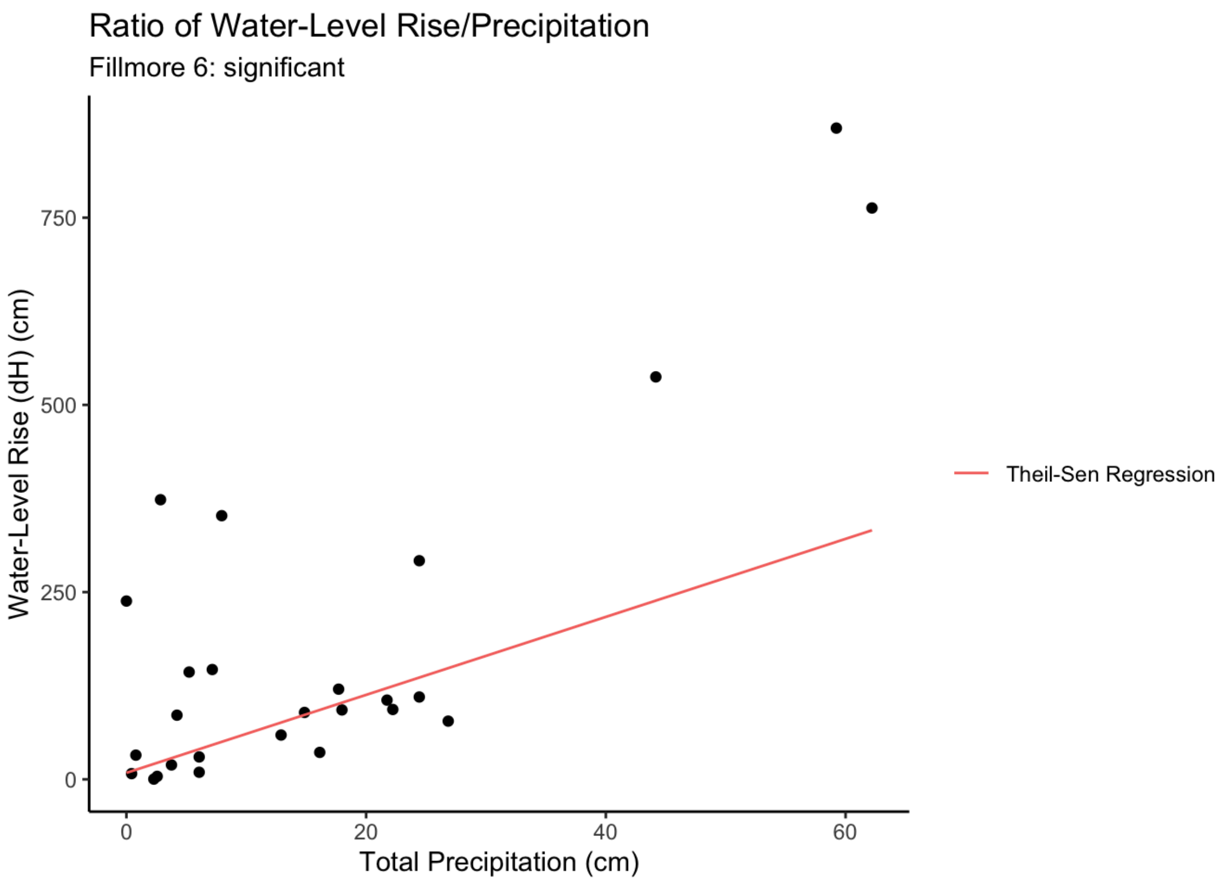
	Estimate	t-value	p-value
Mean dH/precipitation	2.469	1.438	0.169



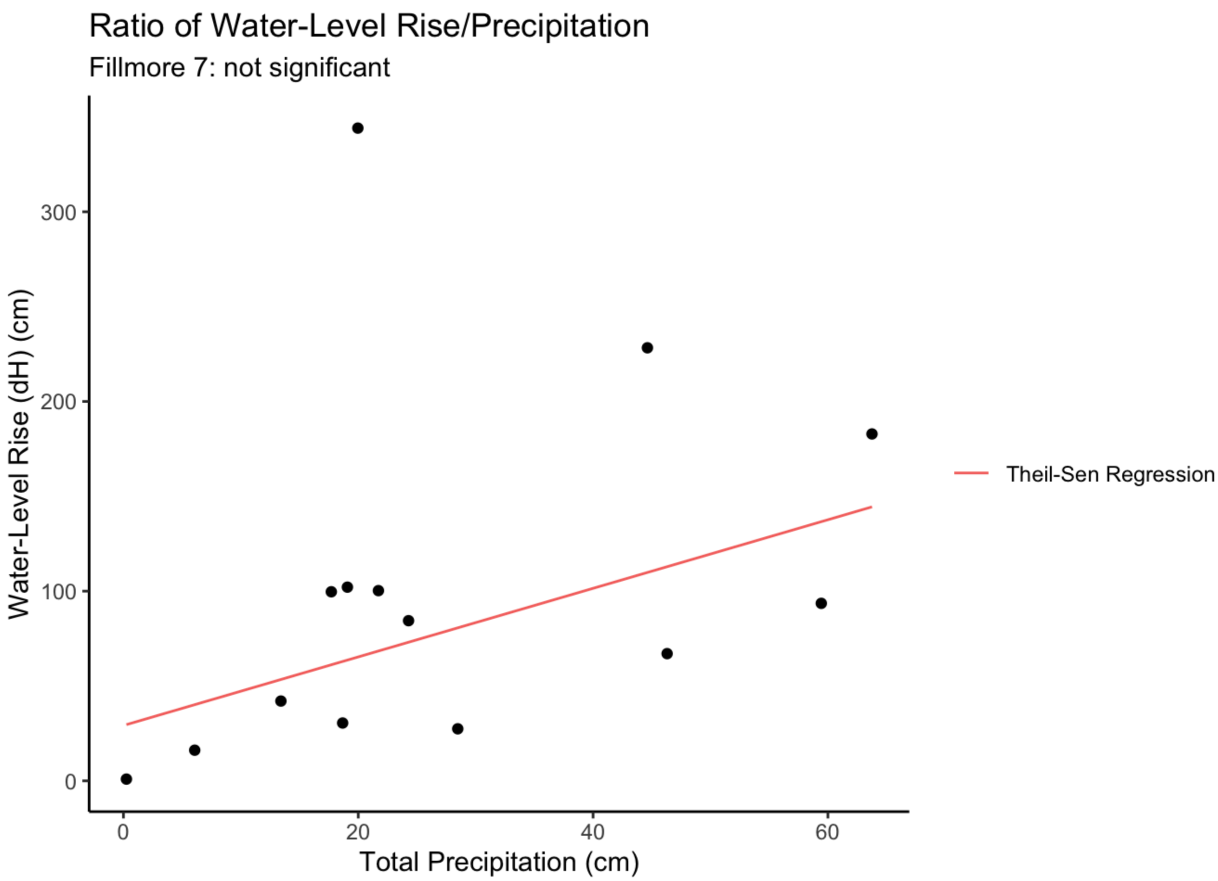
	Estimate	t-value	p-value
Mean dH/precipitation	14.063	9.413	9.76e-11



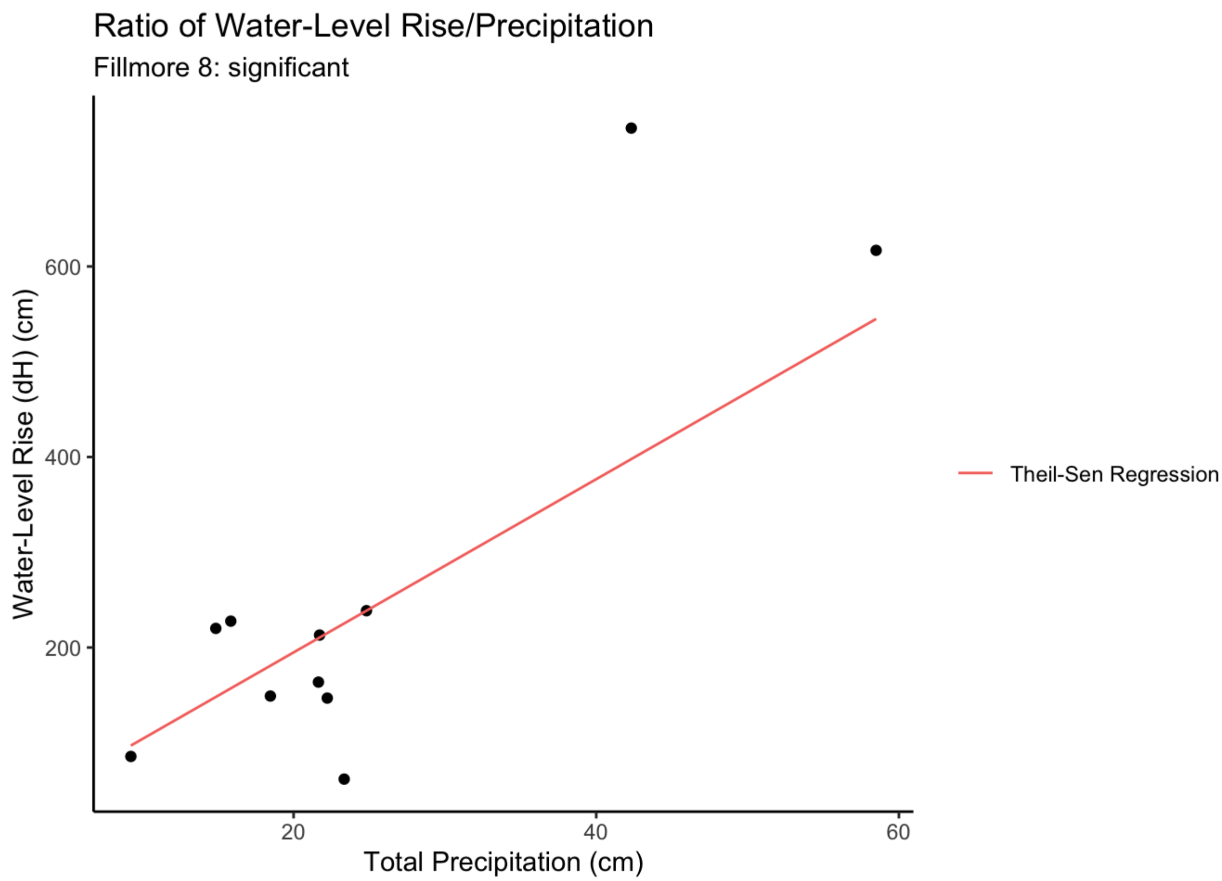
	Estimate	t-value	p-value
Mean dH/precipitation	3.186	1.714	0.101



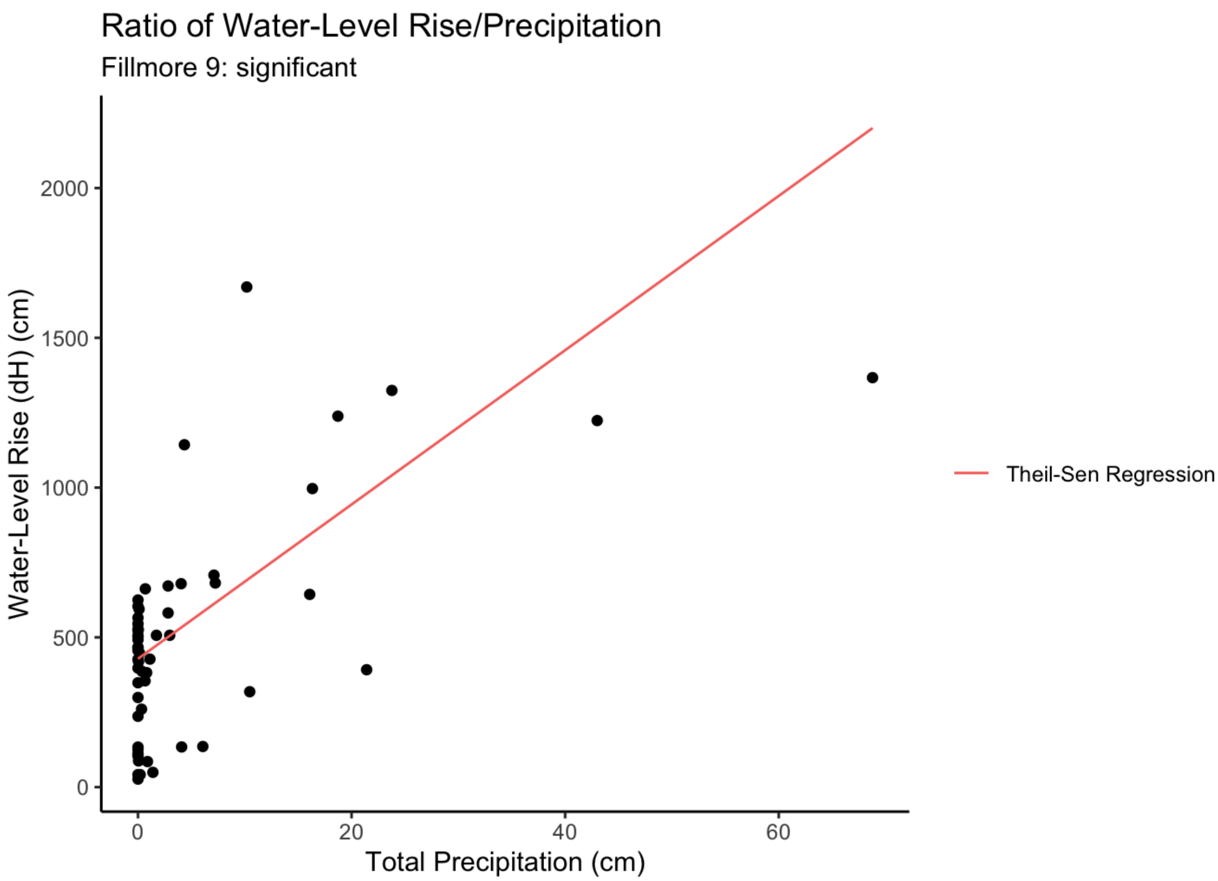
	Estimate	t-value	p-value
Mean dH/precipitation	5.207	2.266	0.0328



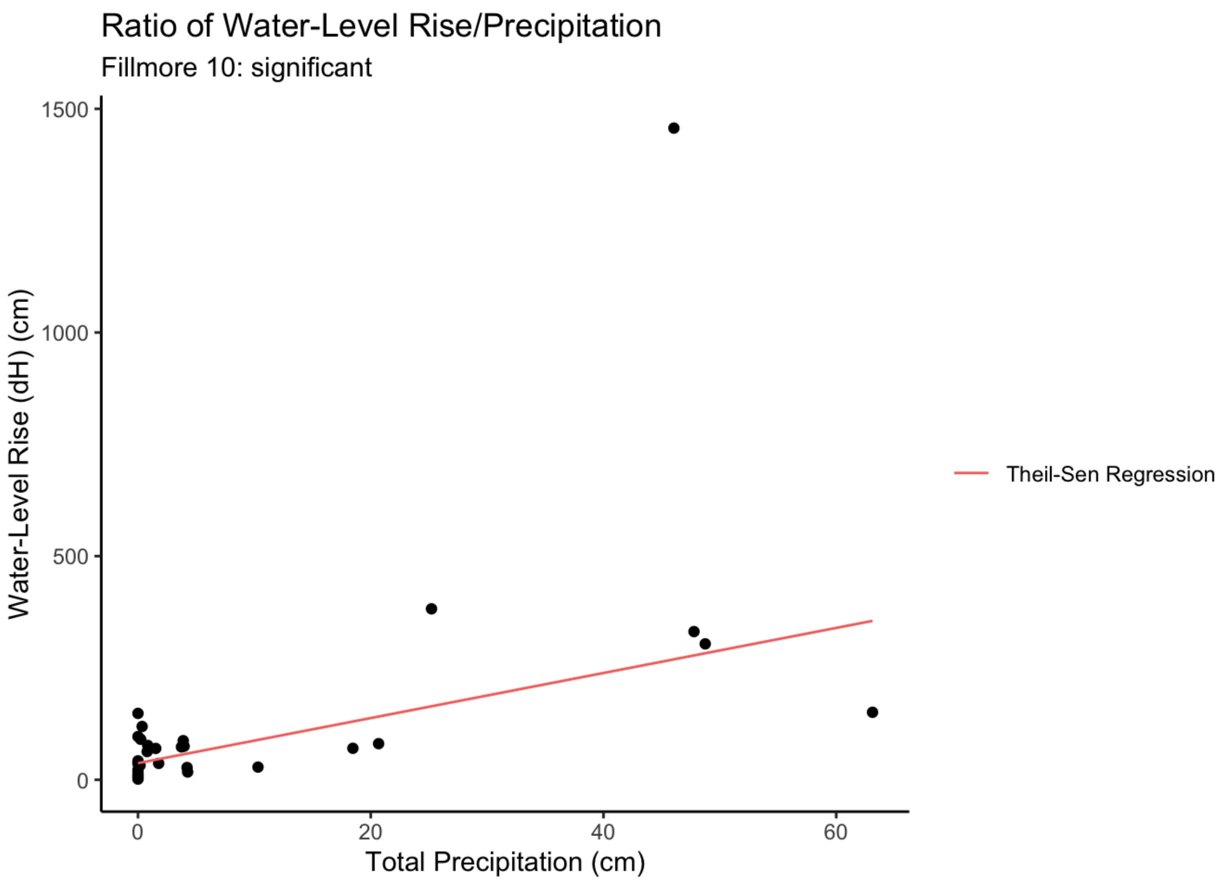
	Estimate	t-value	p-value
Mean dH/precipitation	1.808	1.318	0.212



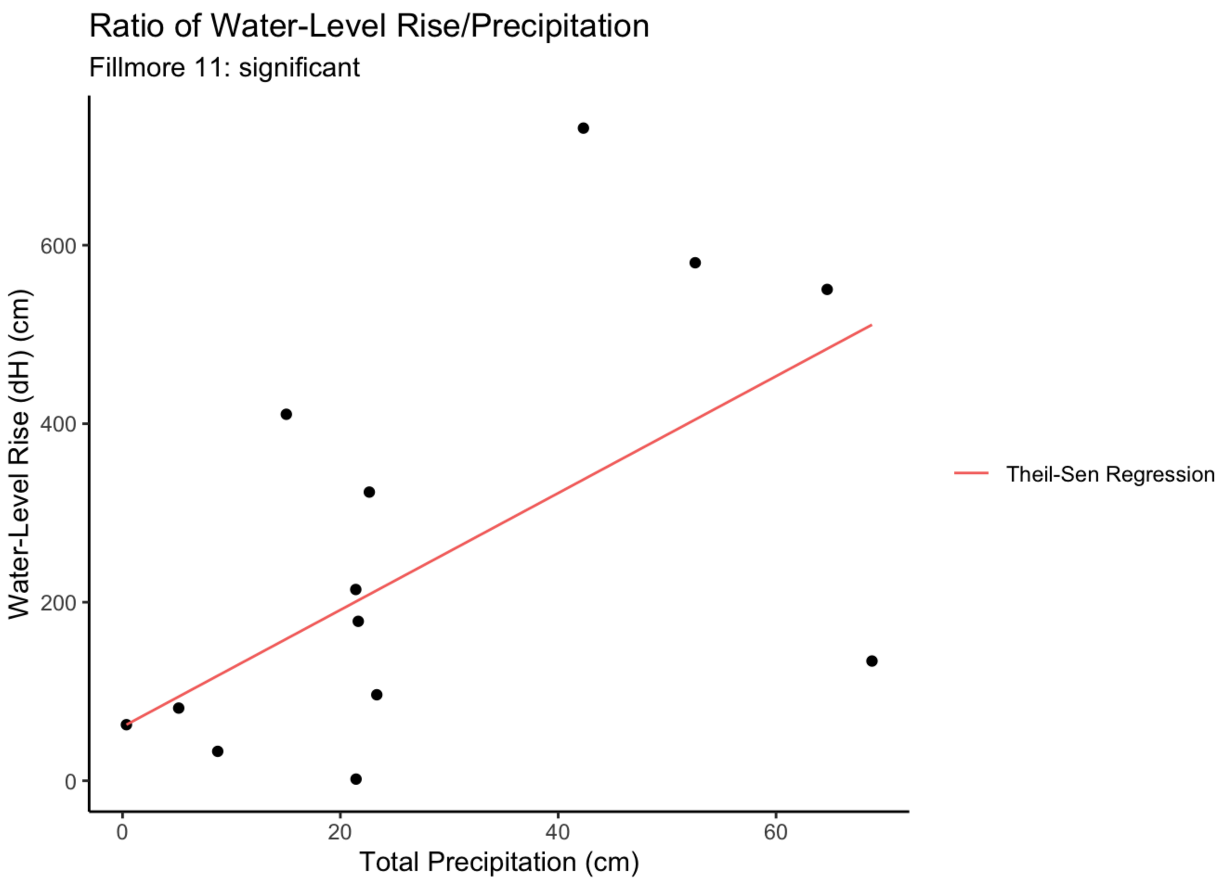
	Estimate	t-value	p-value
Mean dH/precipitation	9.094	2.902	0.0175



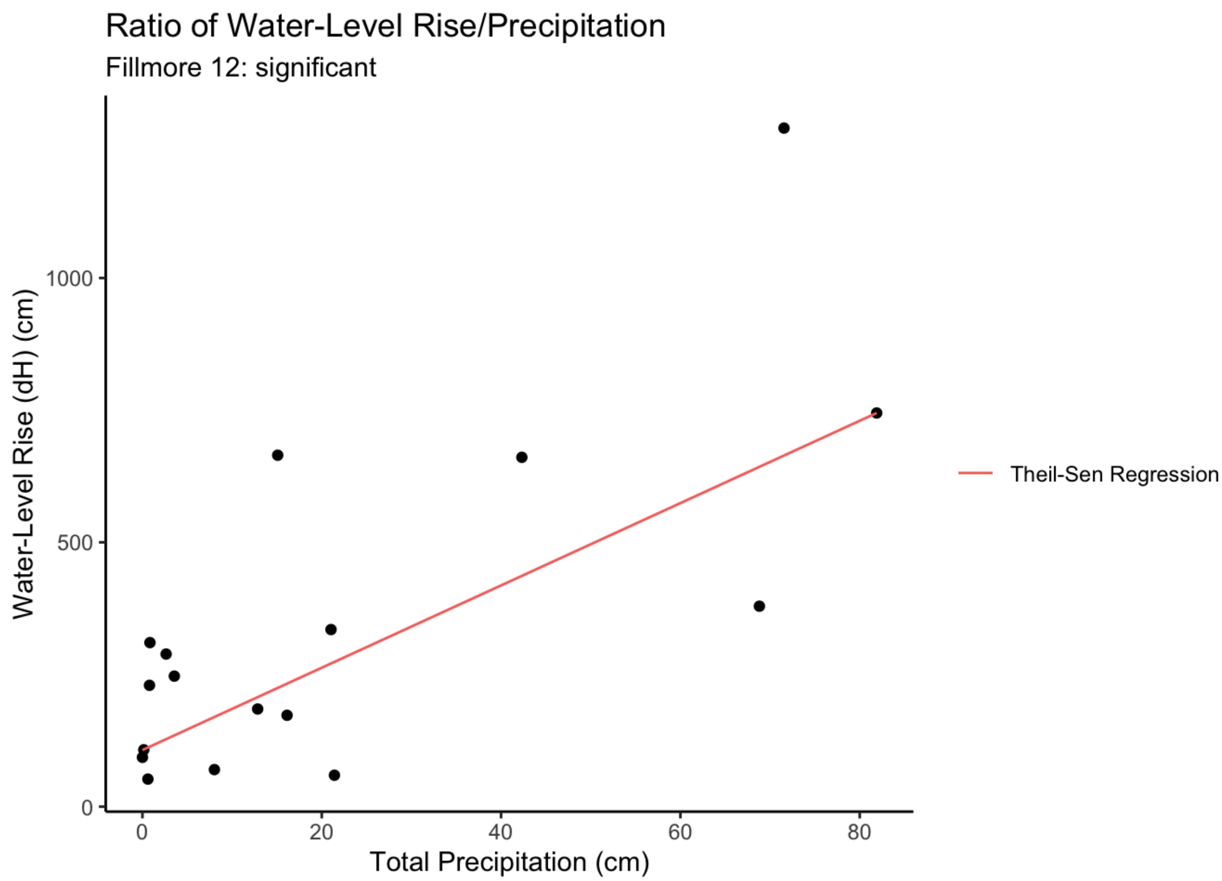
	Estimate	t-value	p-value
Mean dH/precipitation	25.756	7.51	4.97e-10



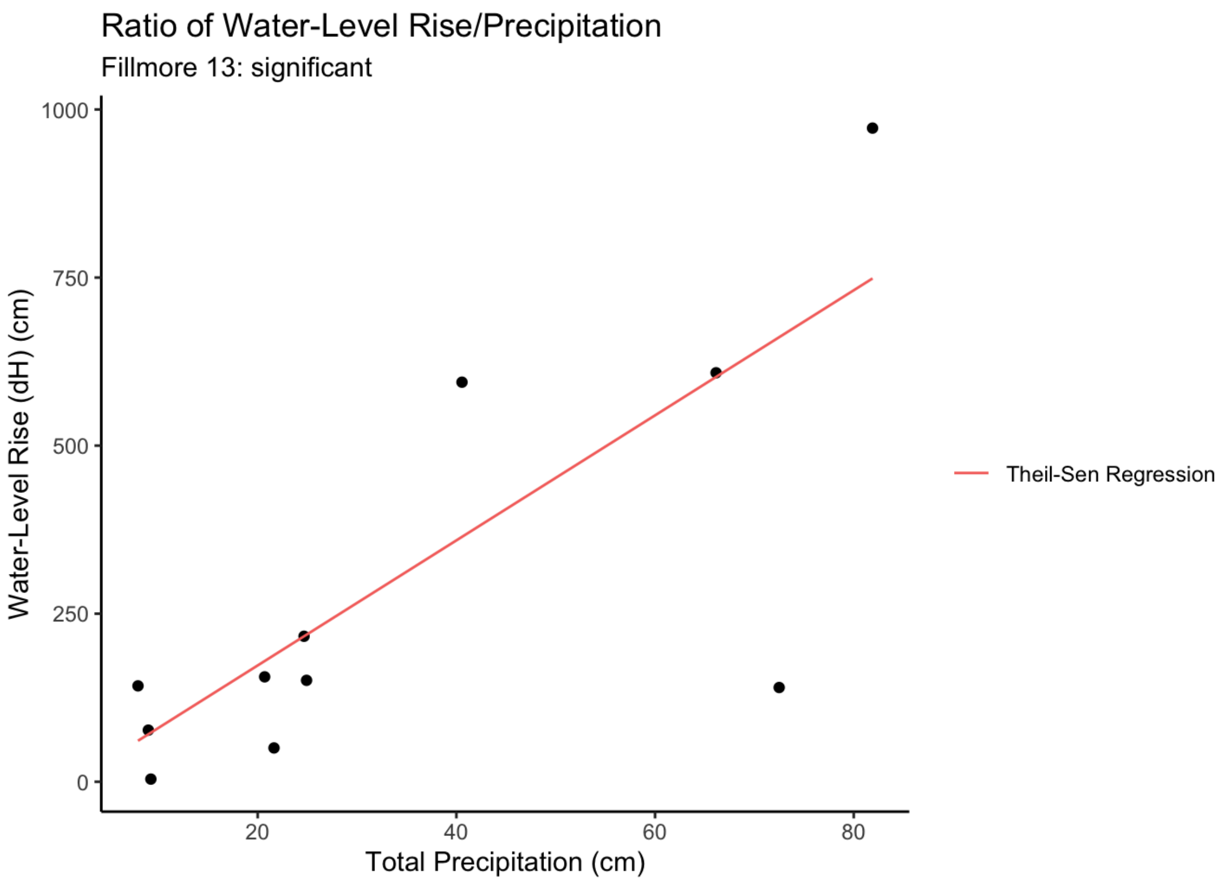
	Estimate	t-value	p-value
Mean dH/precipitation	5.040	2.153	0.0395



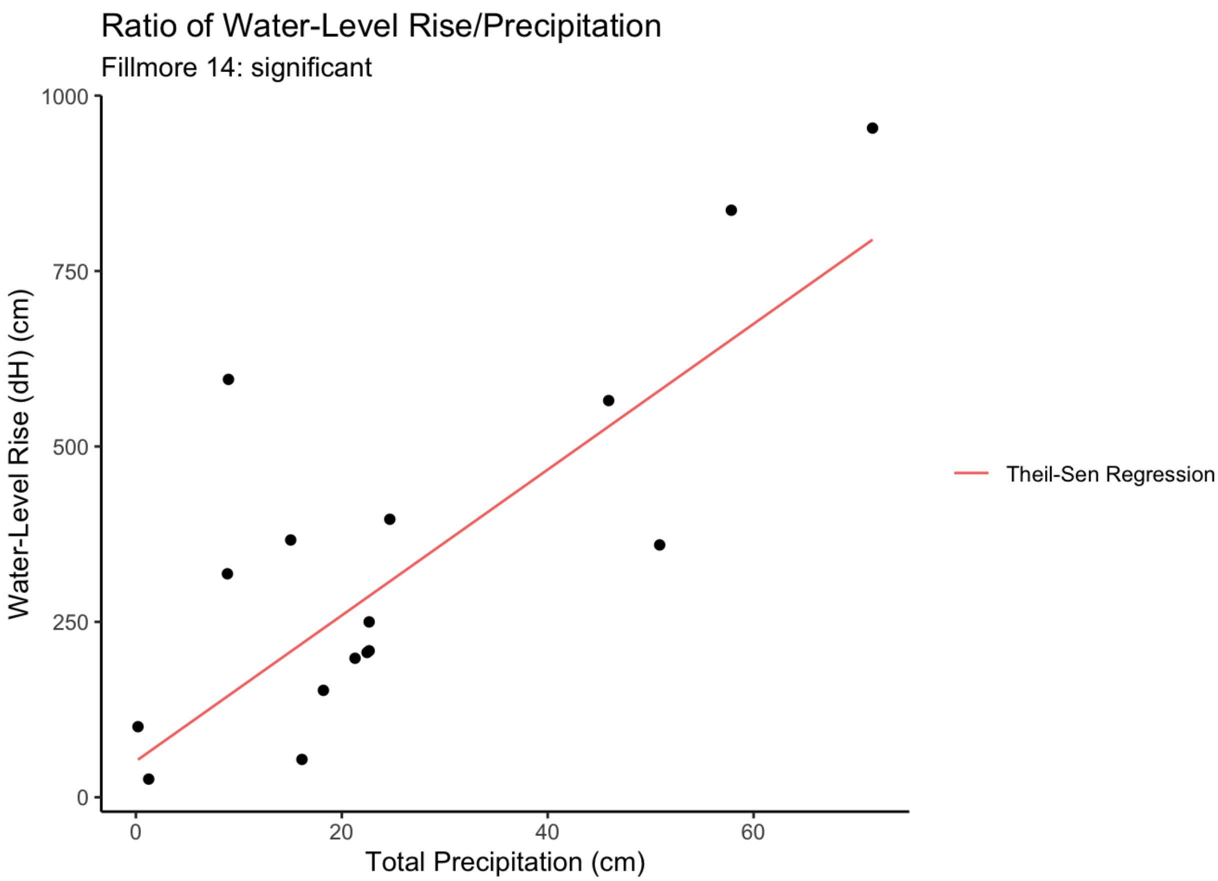
	Estimate	t-value	p-value
Mean dH/precipitation	6.546	2.416	0.0342



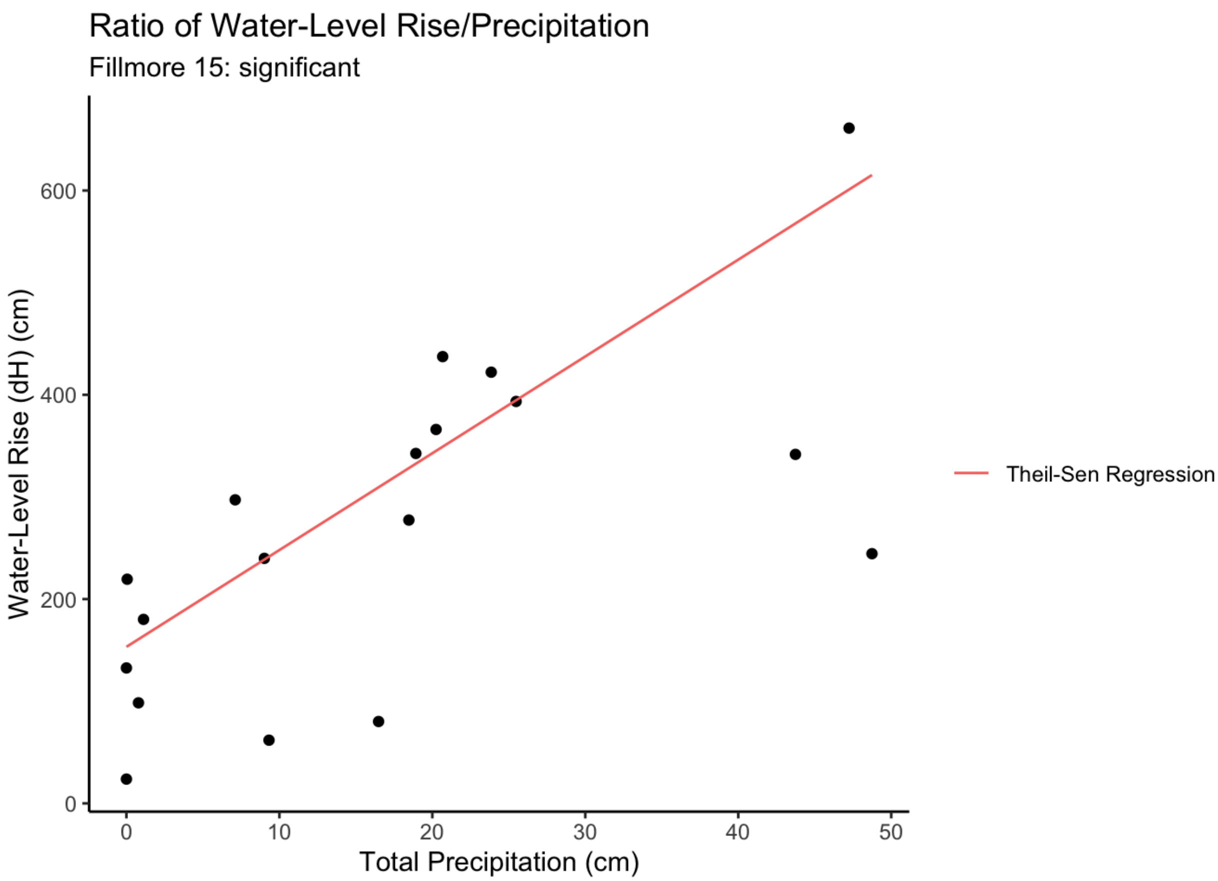
	Estimate	t-value	p-value
Mean dH/precipitation	7.786	3.576	0.00276



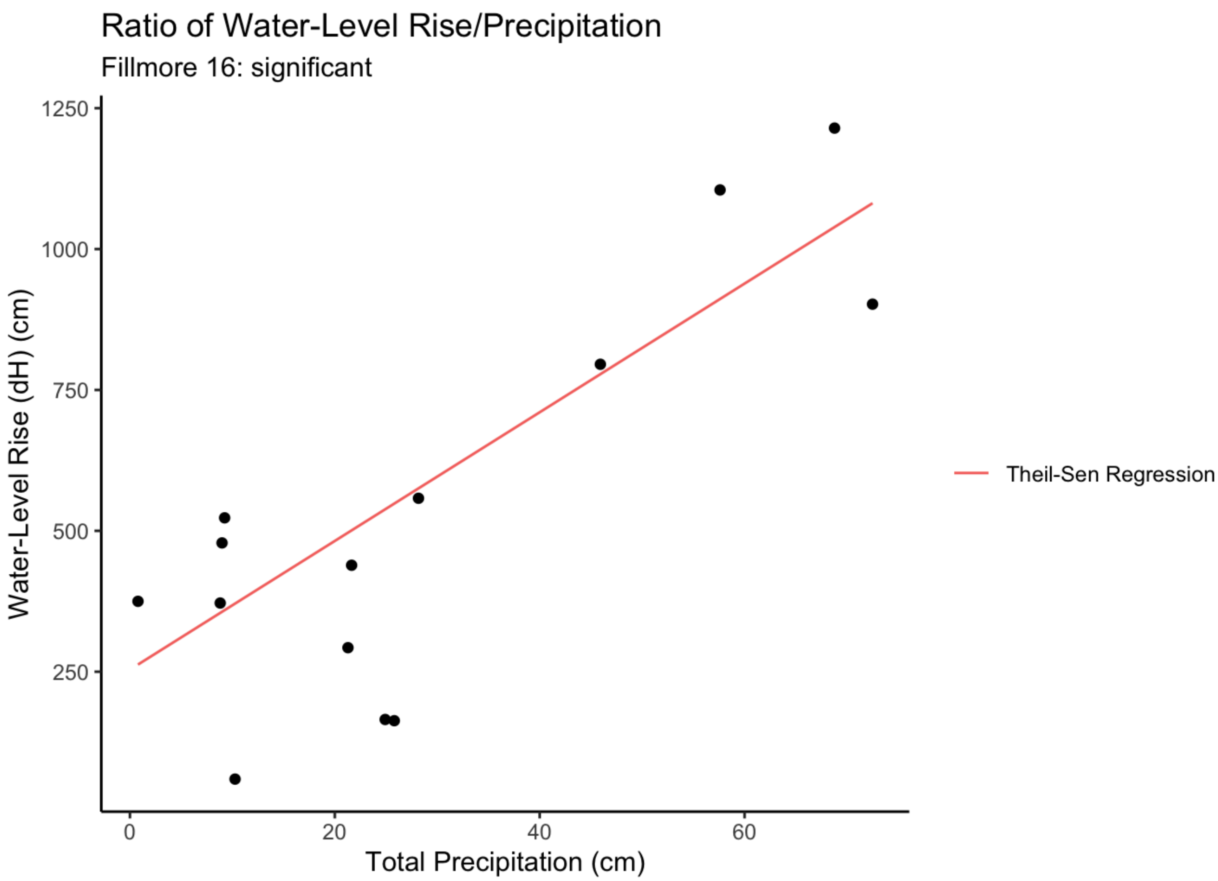
	Estimate	t-value	p-value
Mean dH/precipitation	9.301	3.714	0.00482



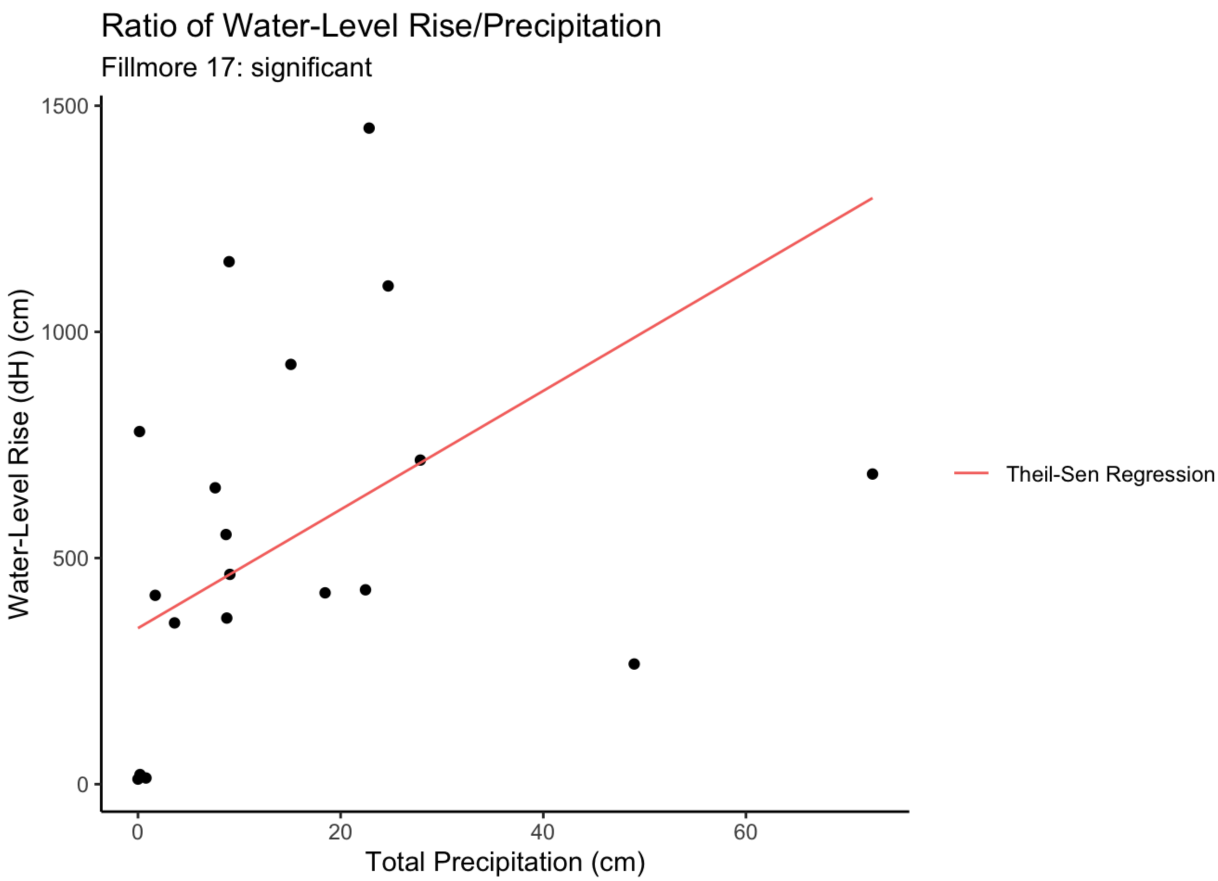
	Estimate	t-value	p-value
Mean dH/precipitation	10.387	4.683	0.000352



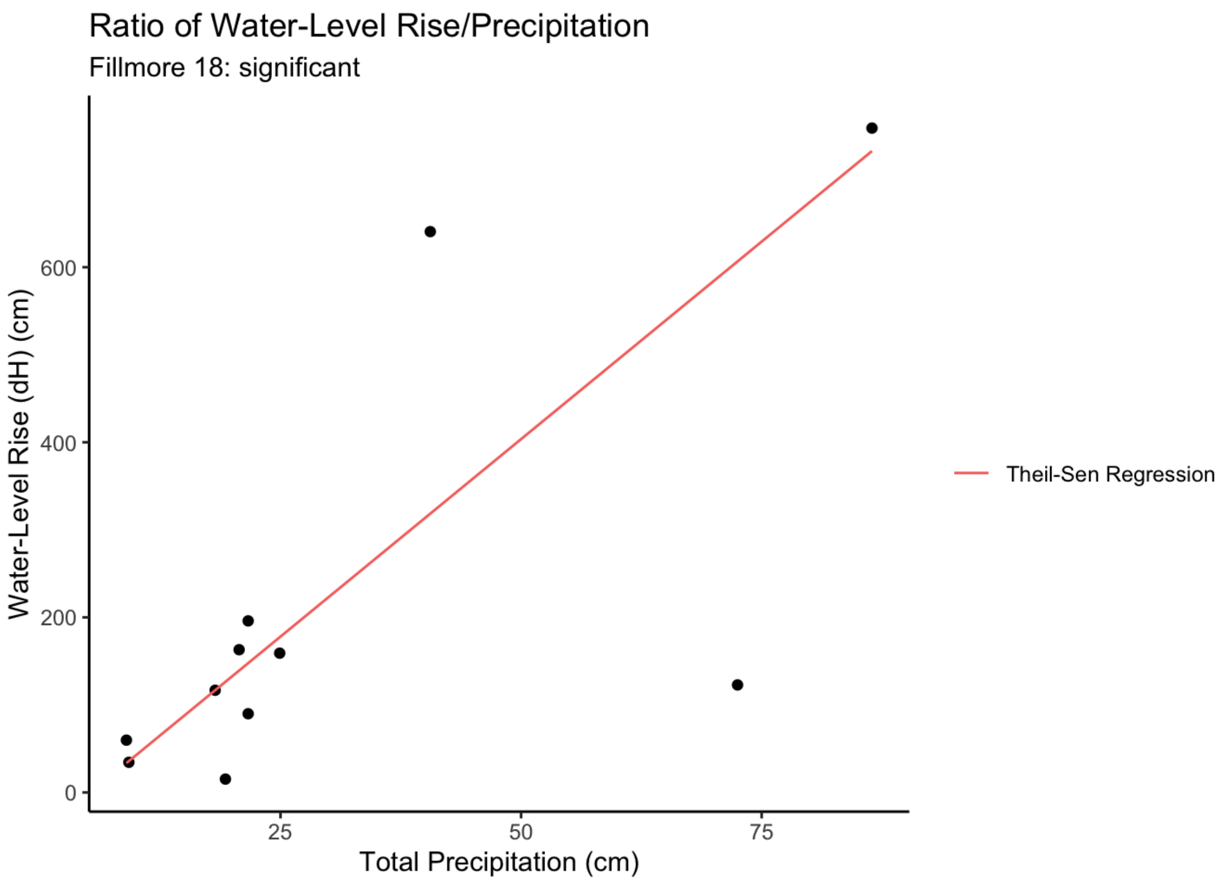
	Estimate	t-value	p-value
Mean dH/precipitation	9.477	4.429	0.000421



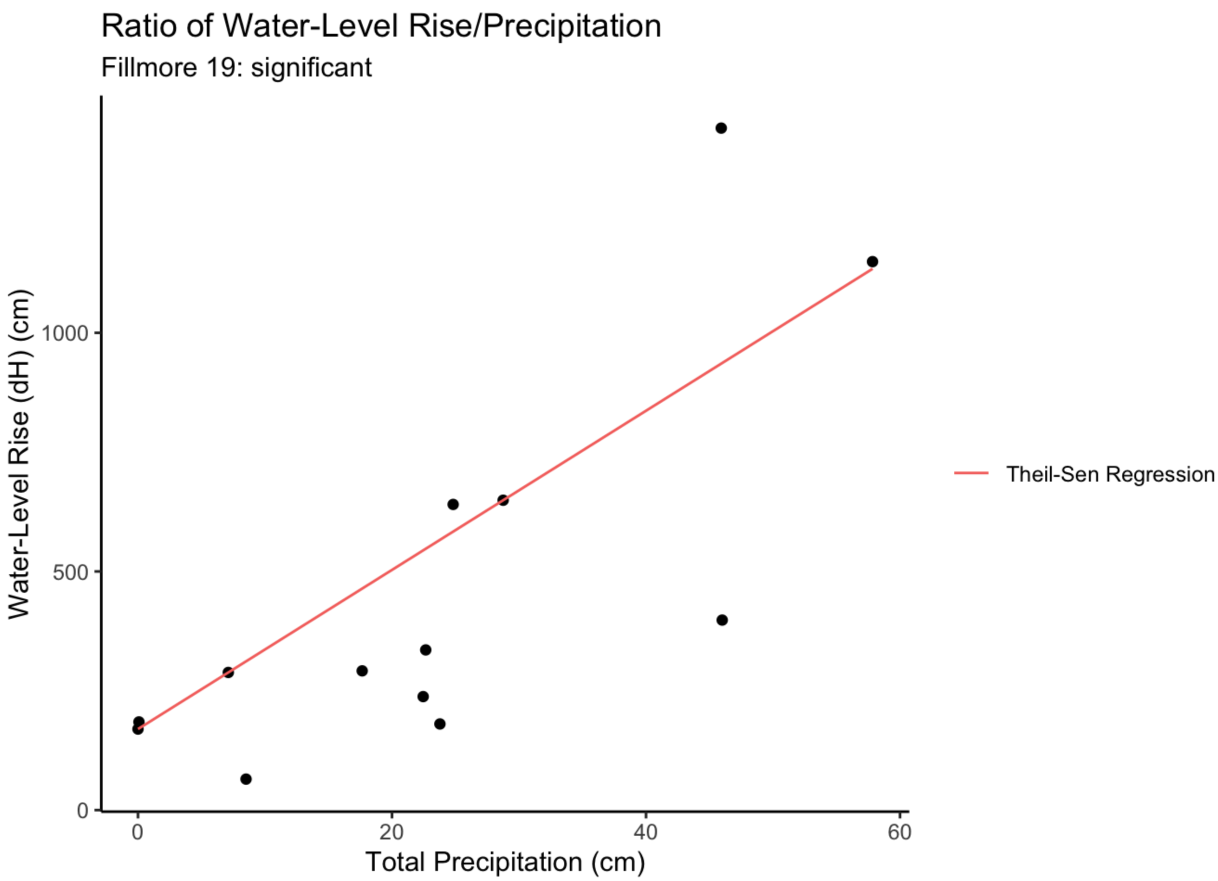
	Estimate	t-value	p-value
Mean dH/precipitation	11.417	4.344	0.000955



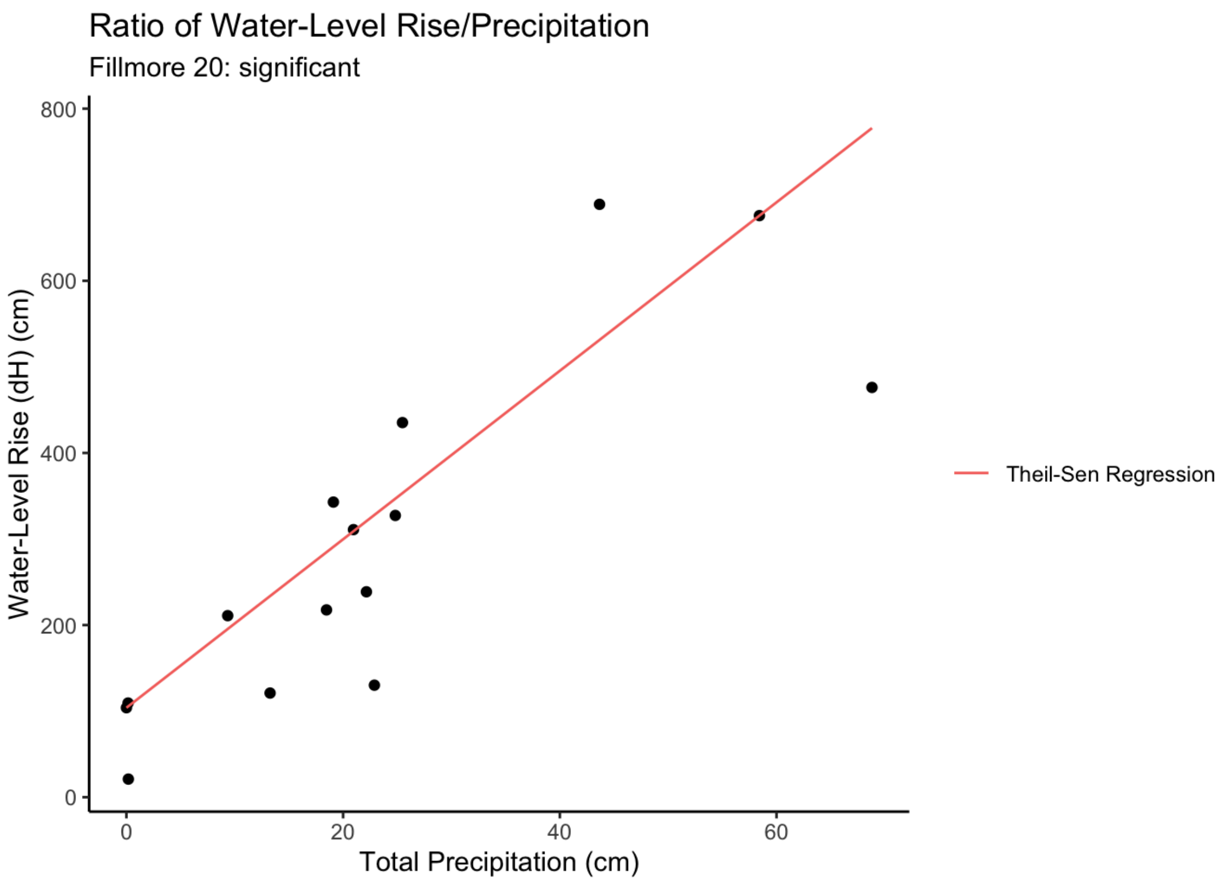
	Estimate	t-value	p-value
Mean dH/precipitation	13.118	2.454	0.0252



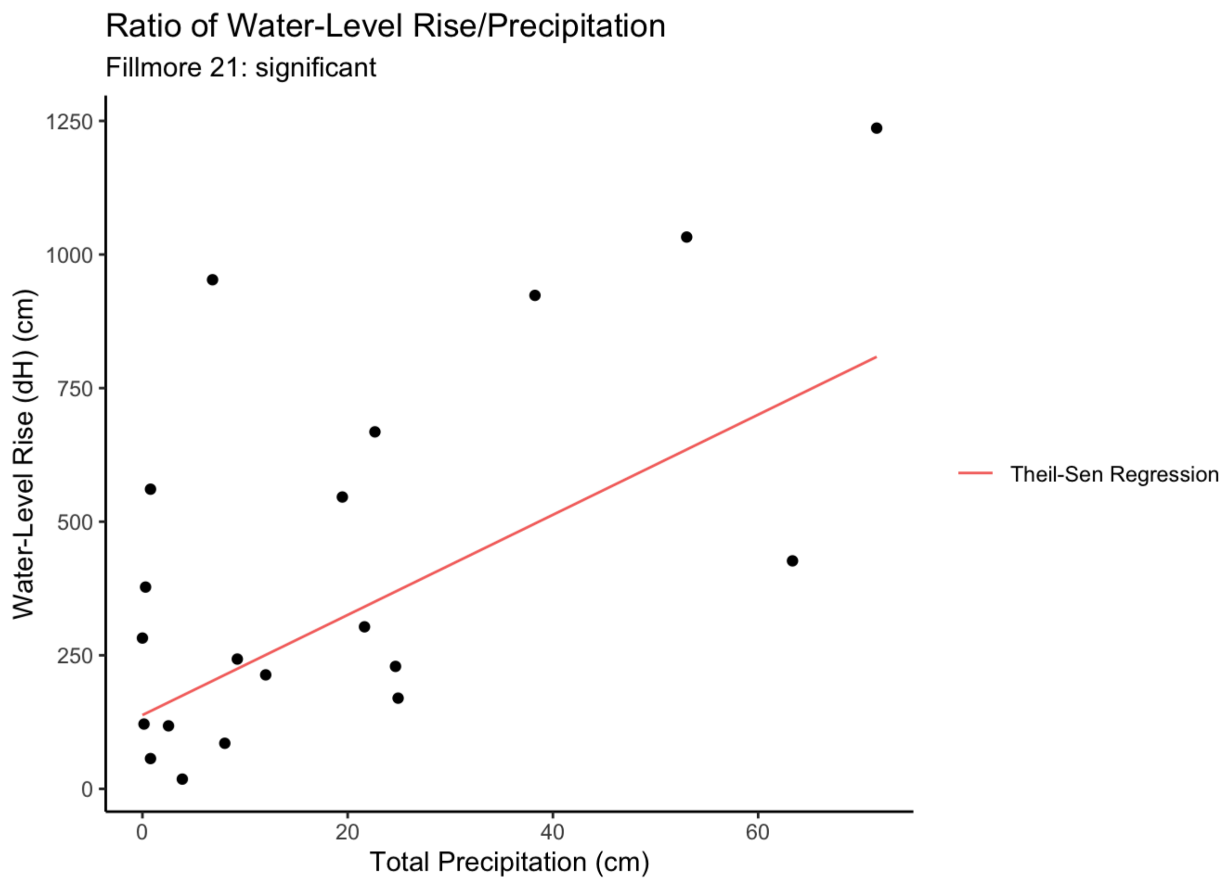
	Estimate	t-value	p-value
Mean dH/precipitation	9.026	3.638	0.00542



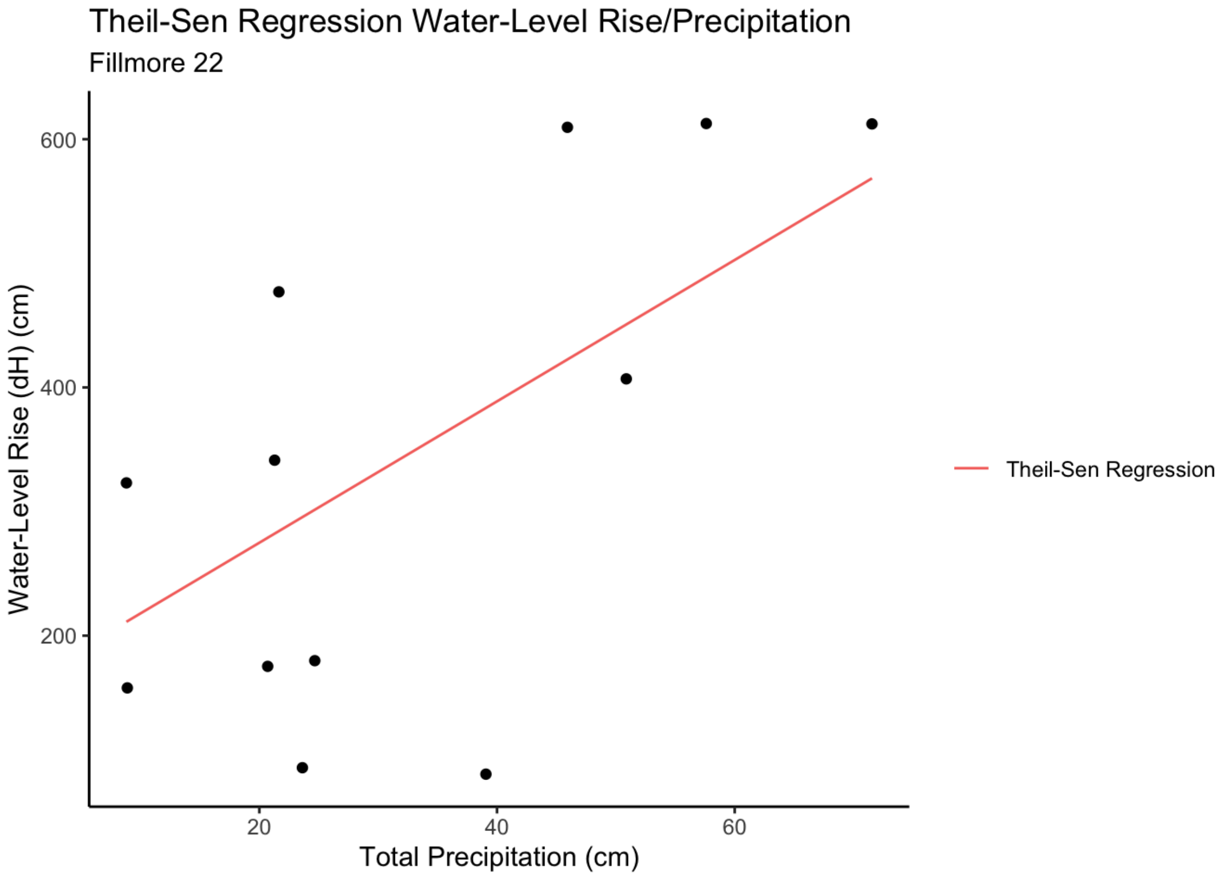
	Estimate	t-value	p-value
Mean dH/precipitation	16.673	3.585	0.00428



	Estimate	t-value	p-value
Mean dH/precipitation	9.788	6.011	0.0000437



	Estimate	t-value	p-value
Mean dH/precipitation	9.370	2.894	0.00967



	Estimate	t-value	p-value
Mean dH/precipitation	5.696	2.316	0.0431

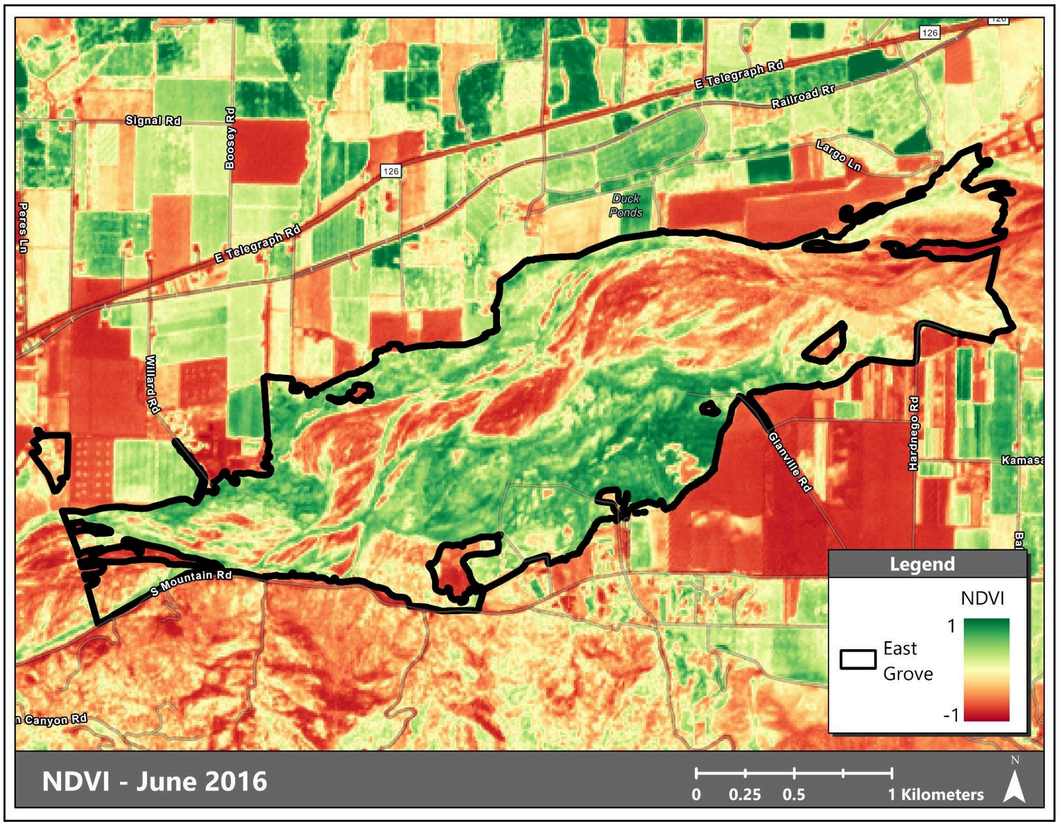
Theil-Sen Water-Level Rise (dH) to Precipitation Rations for All 22 Fillmore Subbasin Wells

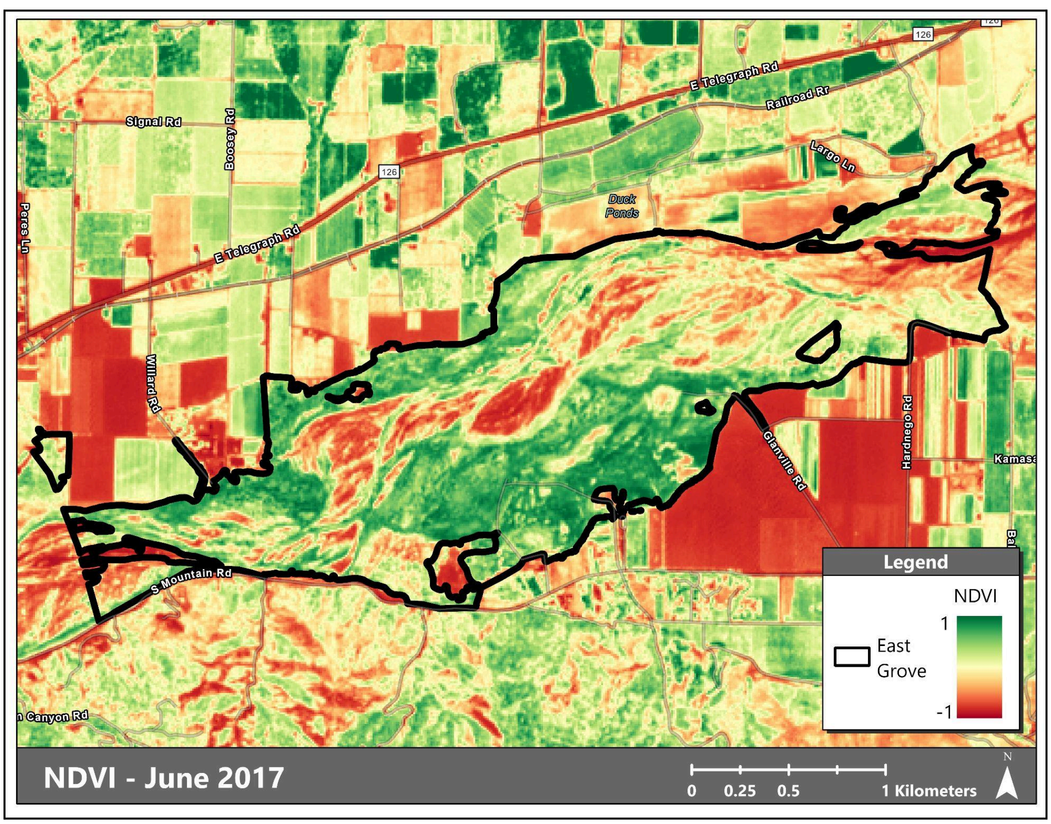
well_id	ratio_slope	ratio_p
Fill 1	5.73609277430865	4.02612394043707E-05
Fill 2	4.10654224224454	2.54888562031856E-05
Fill 3	2.46915968820843	0.168661774534442
Fill 4	14.0626654527628	9.76123529322504E-11
Fill 5	3.18612411768817	0.100577467998777
Fill 6	5.2072072072072	0.0327793471376941
Fill 7	1.80784536668561	0.212107847093178
Fill 8	9.09429569266588	0.0175240677656191
Fill 9	25.7560650493202	4.96586936699484E-10
Fill 10	5.04000498504486	0.0395030999667617
Fill 11	6.54625748809062	0.0342427604852901
Fill 12	7.78553736704034	0.00275614091166747
Fill 13	9.30133333333334	0.00481787420417588
Fill 14	10.3874157303371	0.000352272094712116
Fill 15	9.47698825361125	0.000421296597876631
Fill 16	11.4168377823409	0.000955075429025639
Fill 17	13.1180124223602	0.0252061478090487
Fill 18	9.0255737704918	0.00542059776543052
Fill 19	16.6731701161029	0.00428073581266174
Fill 20	9.78782608695651	4.36950782028084E-05
Fill 21	9.37041352952192	0.00967233262422815
Fill 22	5.69564276439186	0.043097877572954

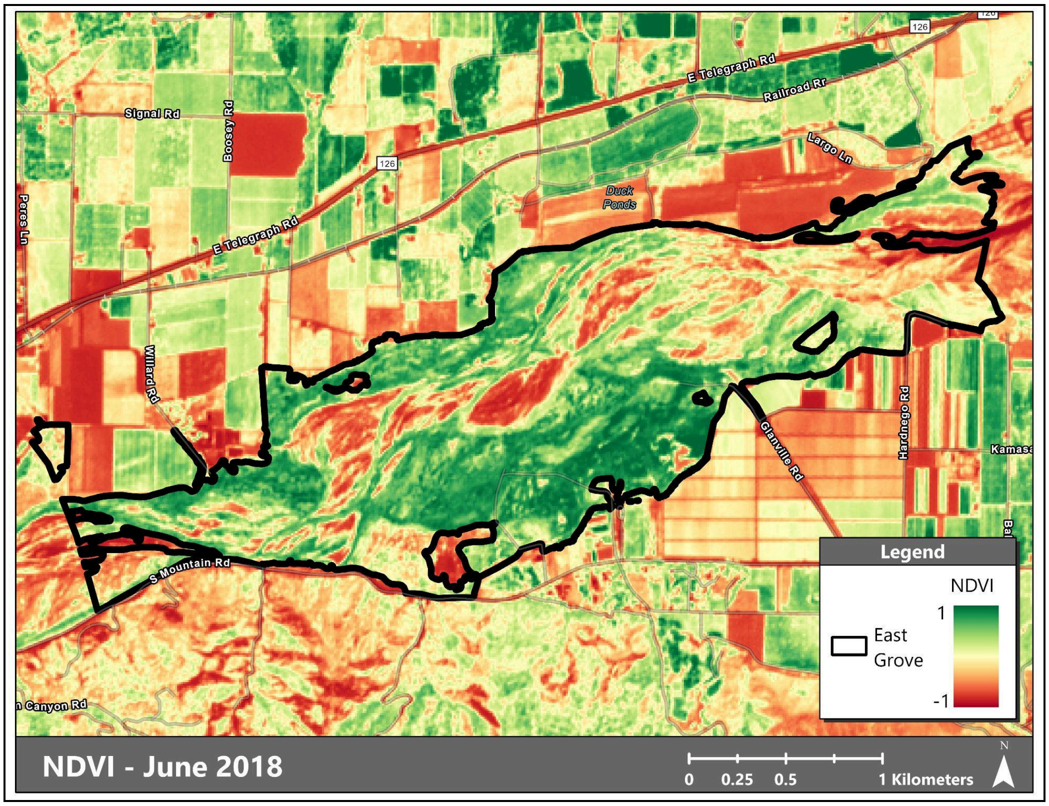
3.3 Remote Sensing

3.3.1 NDVI and NDMI Rasters

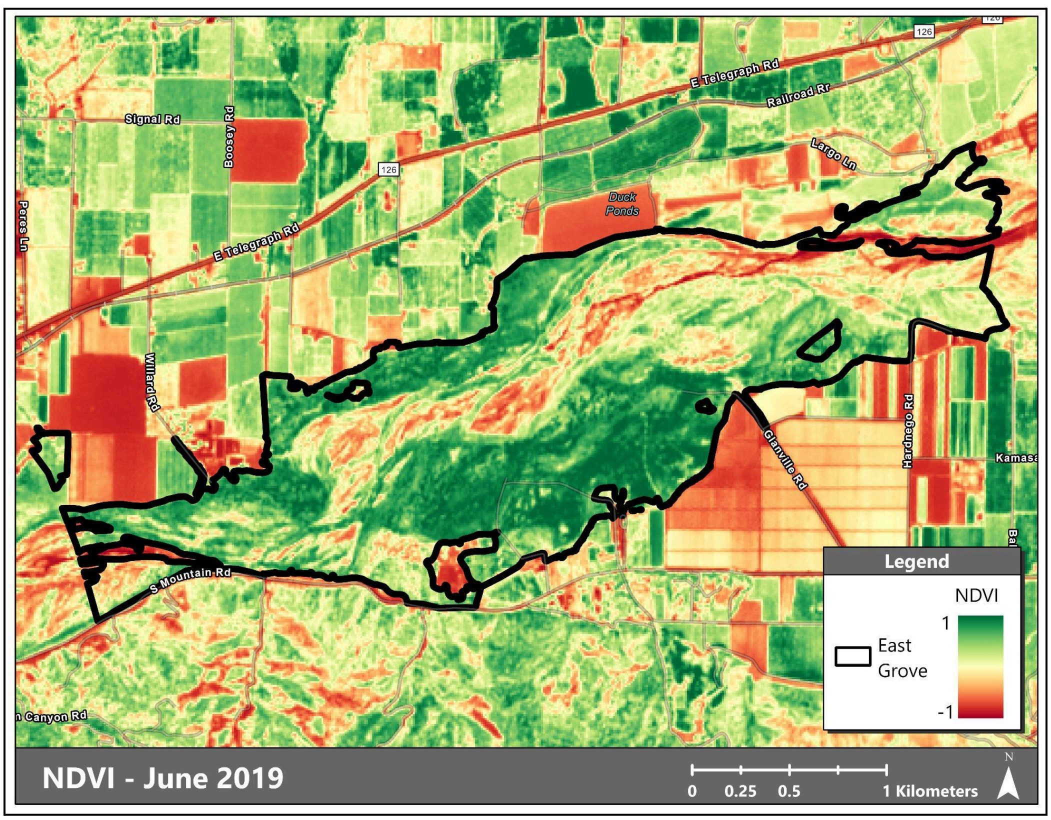
Maps of June NDVI and NDMI for the years 2016 to 2023



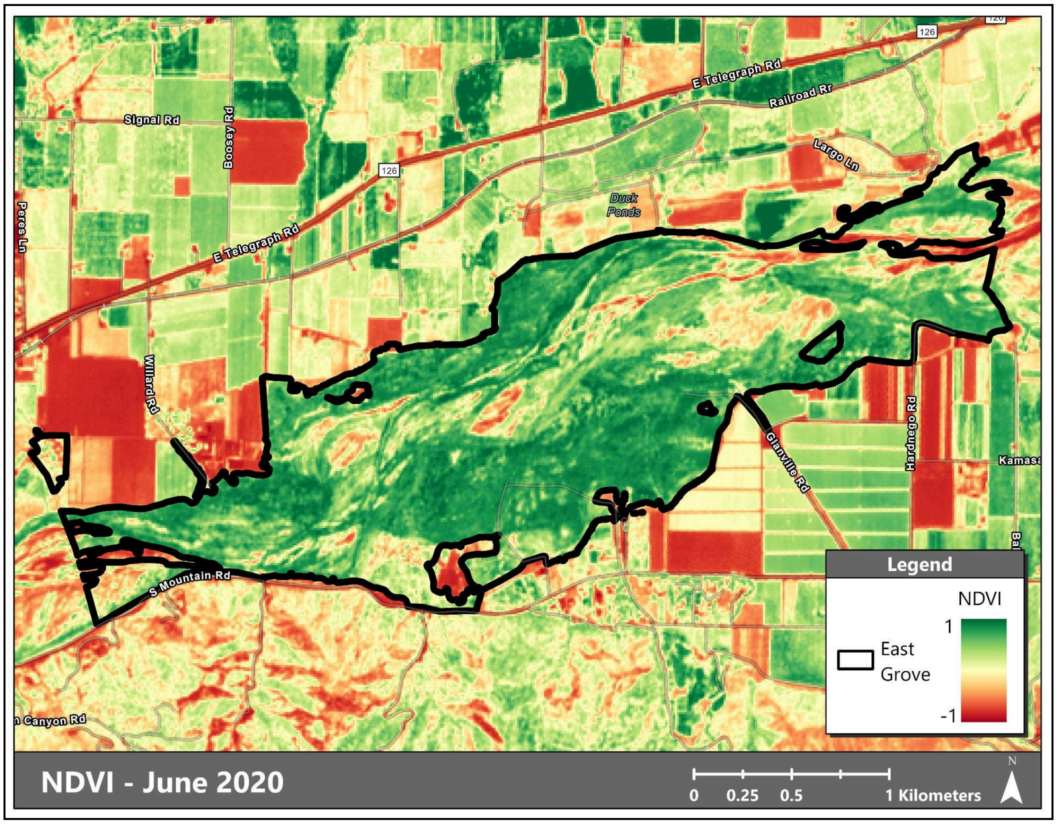


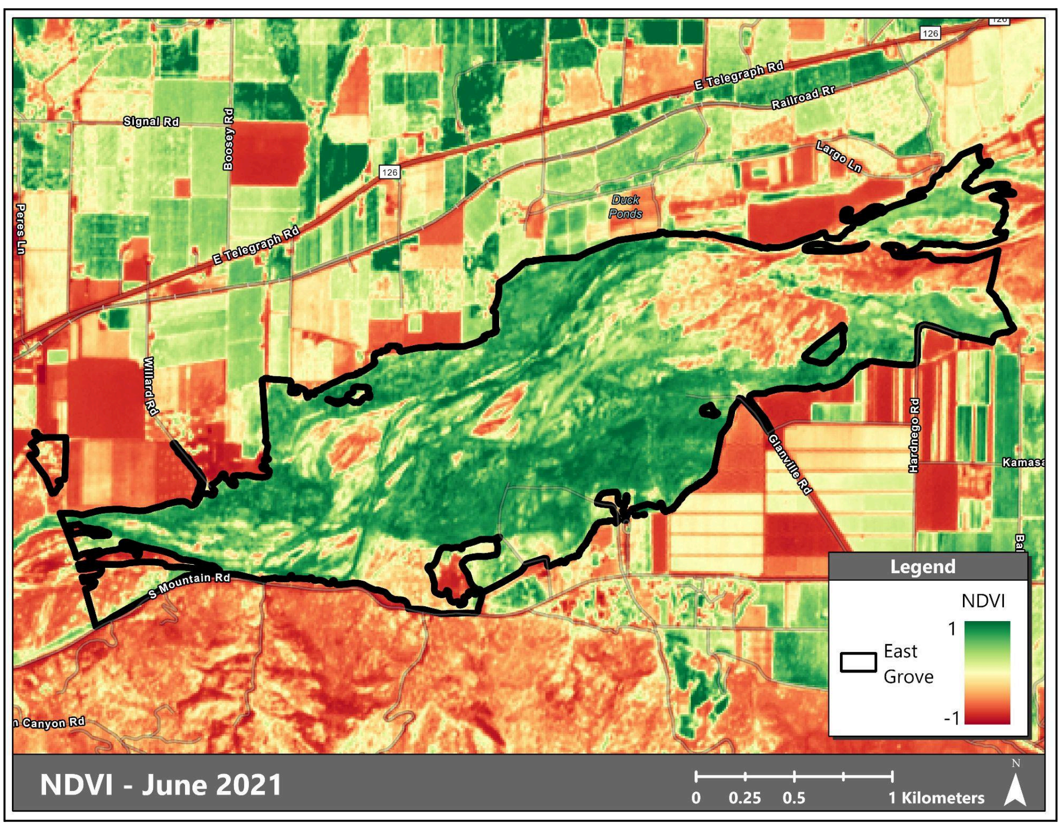


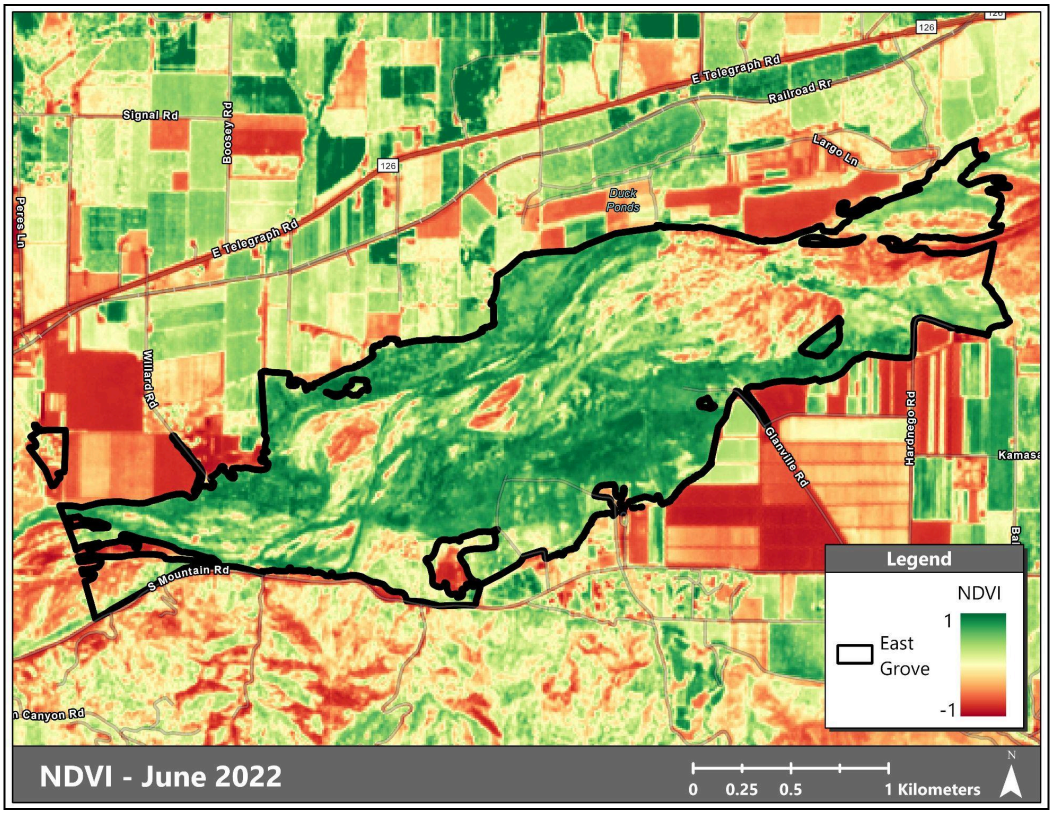
E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
126
Largo Ln
Duck Ponds
Peres Ln
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
n Canyon Rd
Legend
NDVI
1
-1
East Grove
NDVI - June 2018
0
0.25
0.5
1 Kilometers
N

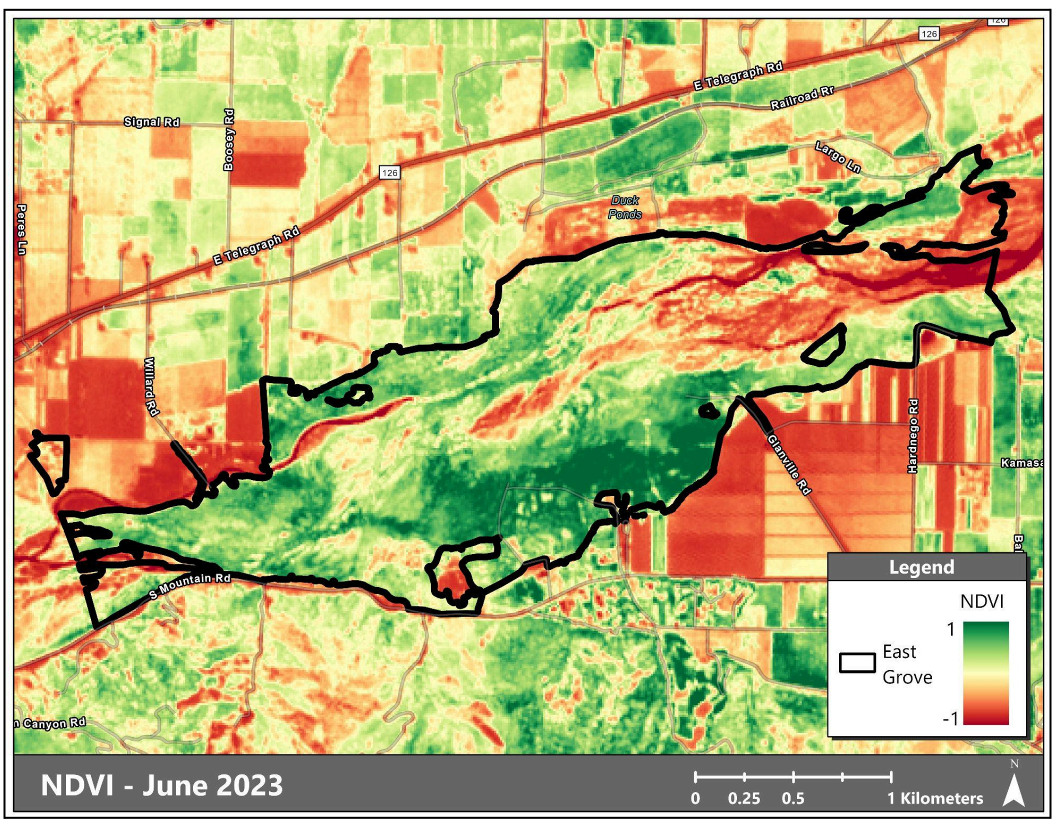


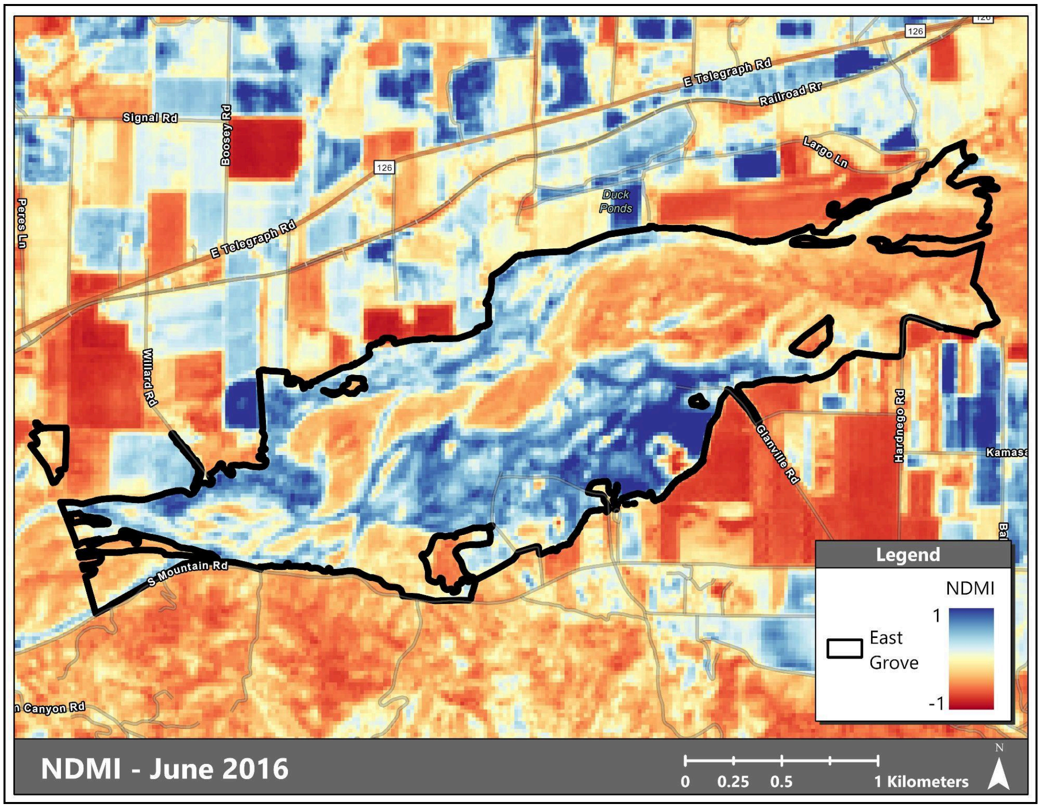
E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
126
Largo Ln
Duck Ponds
Peres Ln
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
n Canyon Rd
Legend
NDVI
1
-1
East Grove
NDVI - June 2019
0
0.25
0.5
1 Kilometers
N


NDVI - June 2020
E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
Largo Ln
Duck Ponds
Peres Ln
Willard Rd
Glanville Rd
Hardnego Rd
S Mountain Rd
Legend
NDVI
East Grove
1
-1
0 0.25 0.5 1 Kilometers
N

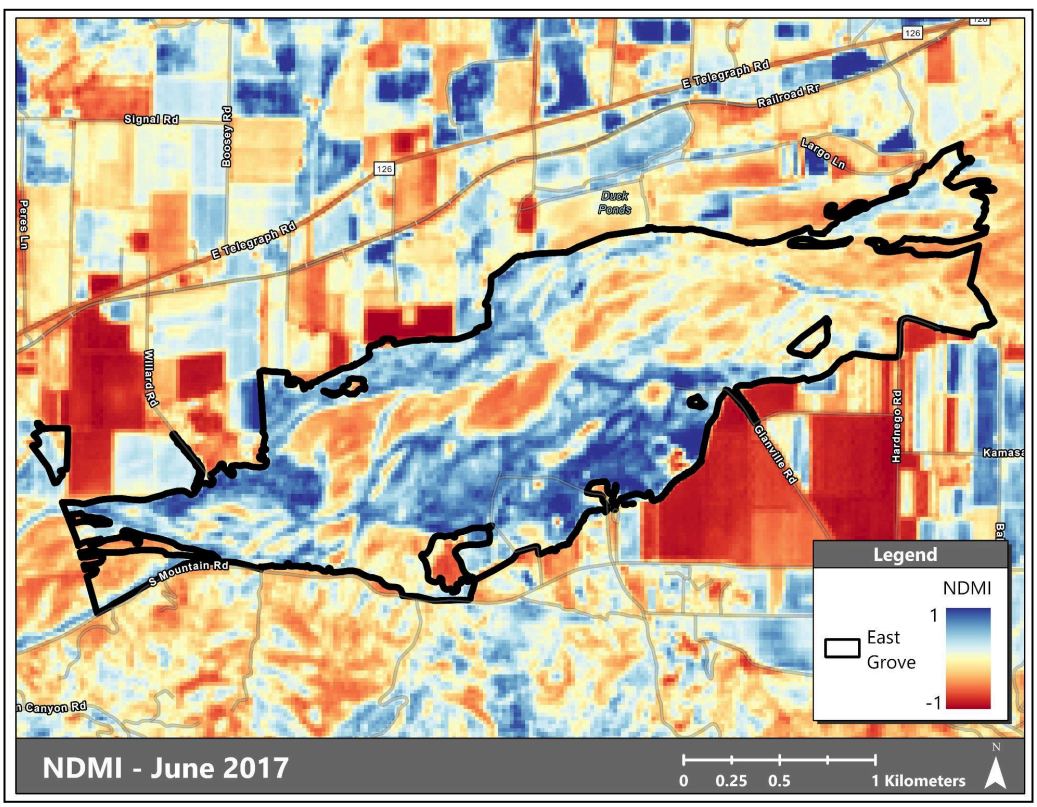

NDVI - June 2021
E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
Largo Ln
Duck Ponds
Peres Ln
Willard Rd
Glanville Rd
Hardnego Rd
S Mountain Rd
Legend
NDVI
East Grove
1
-1
0 0.25 0.5 1 Kilometers
N


E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
126
Largo Ln
Duck Ponds
Peres Ln
E Telegraph Rd
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
Canyon Rd
Legend
NDVI
1
-1
East Grove
NDVI - June 2022
0 0.25 0.5 1 Kilometers
N

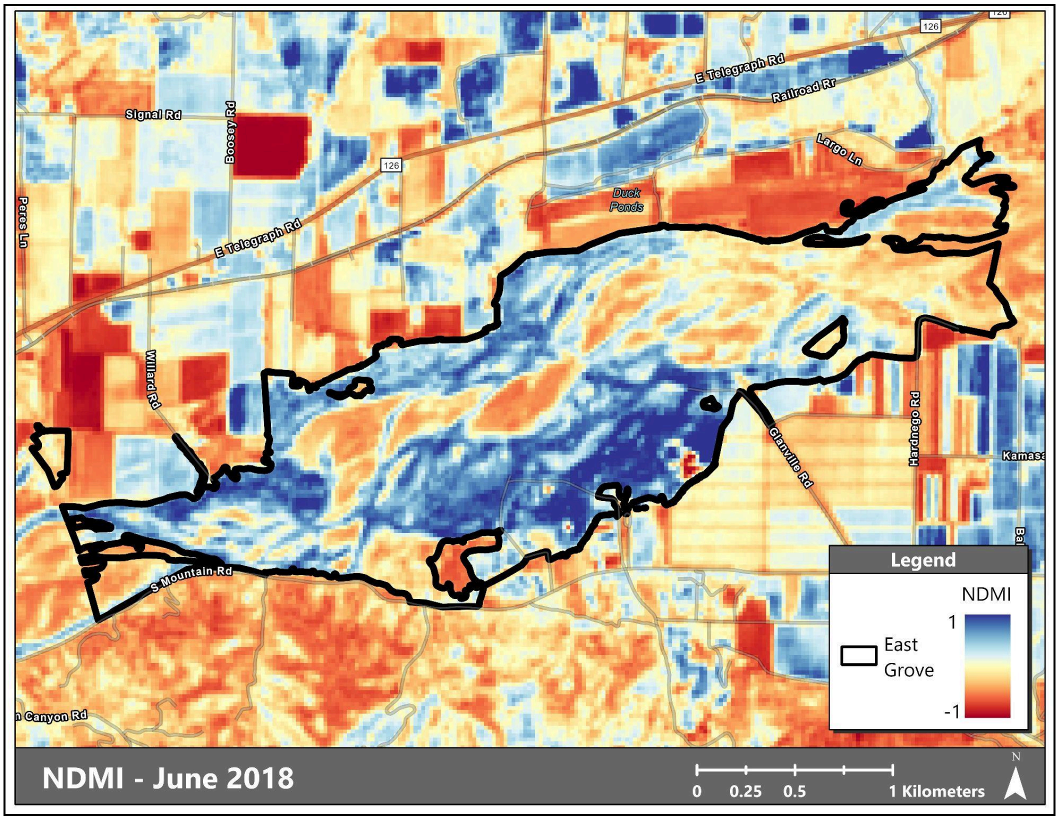

E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
126
Largo Ln
Duck Ponds
Peres Ln
E Telegraph Rd
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
Canyon Rd
Legend
NDVI
1
-1
East Grove
NDVI - June 2023
0 0.25 0.5 1 Kilometers
N

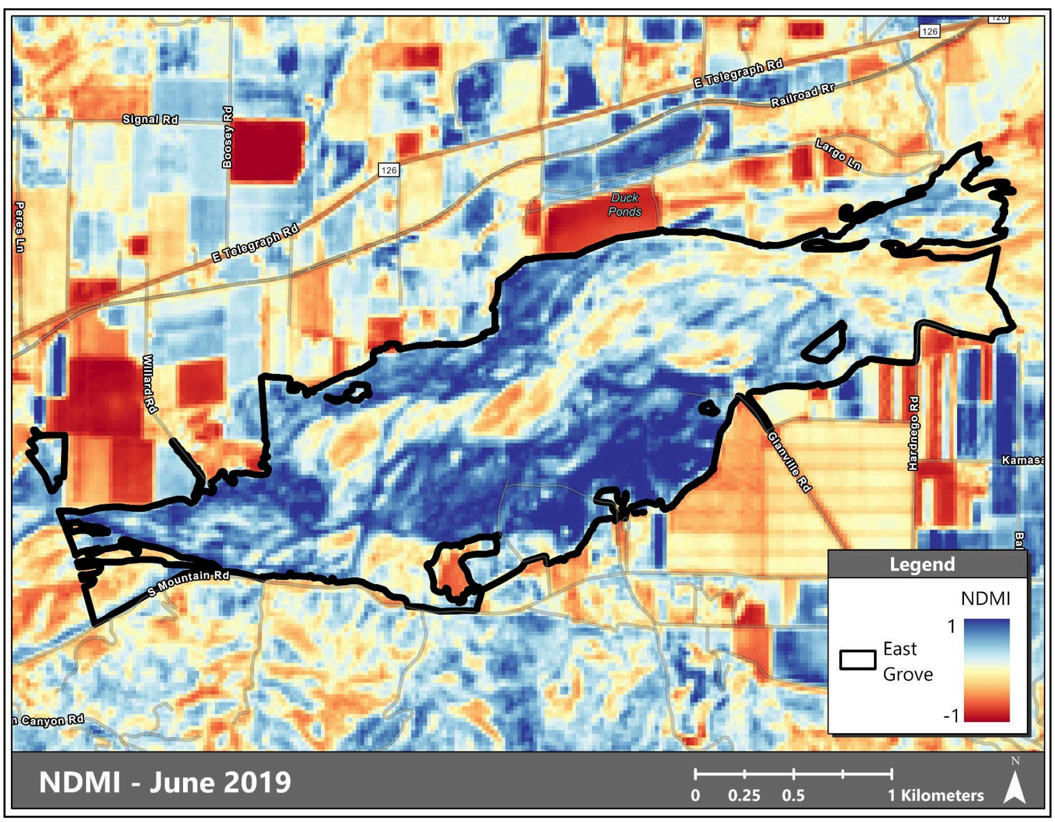


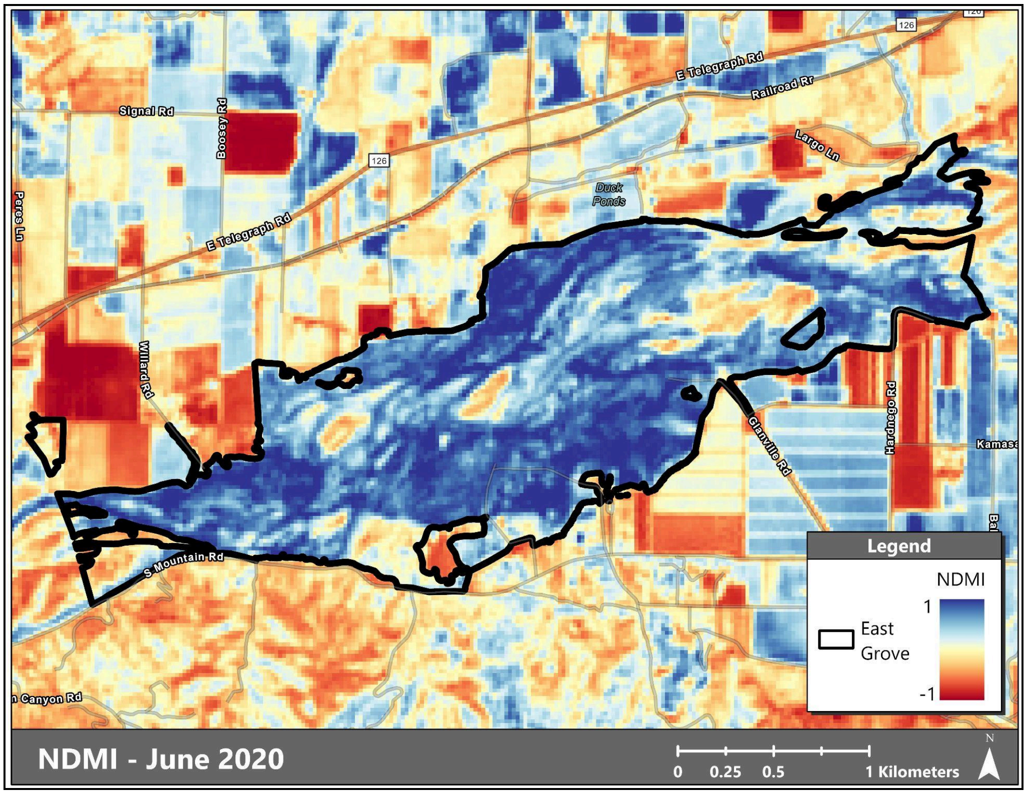
126
E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
Largo Ln
Duck Ponds
Peres Ln
E Telegraph Rd
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
n Canyon Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2016
0 0.25 0.5 1 Kilometers
N

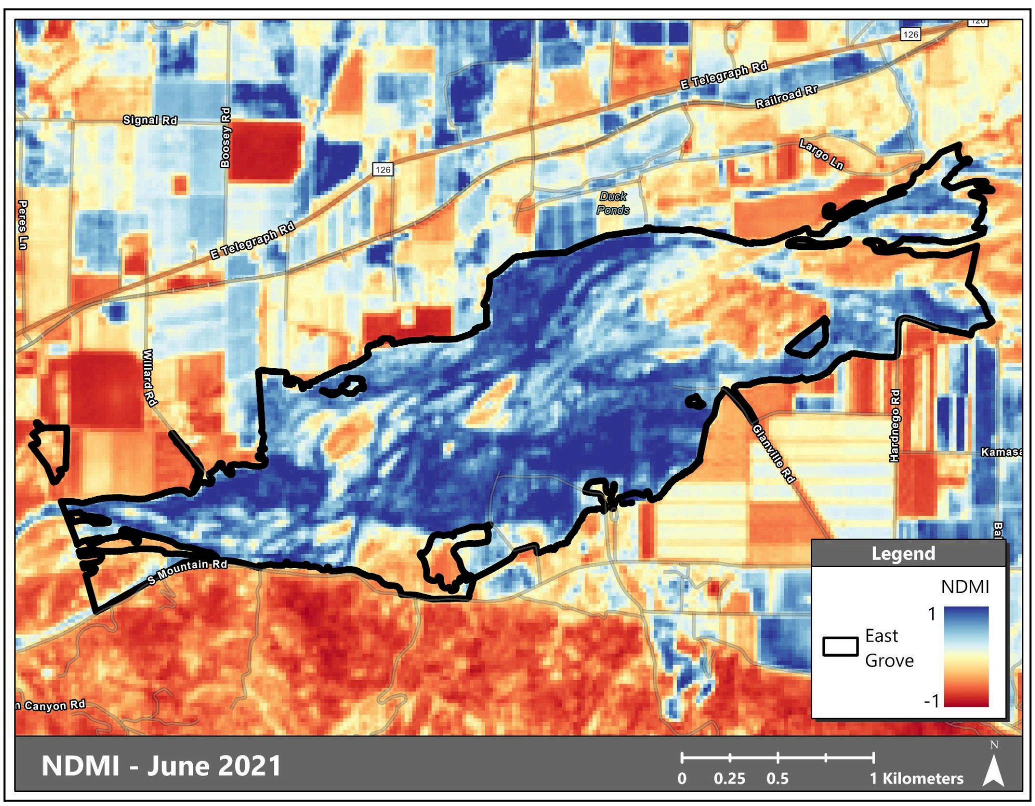


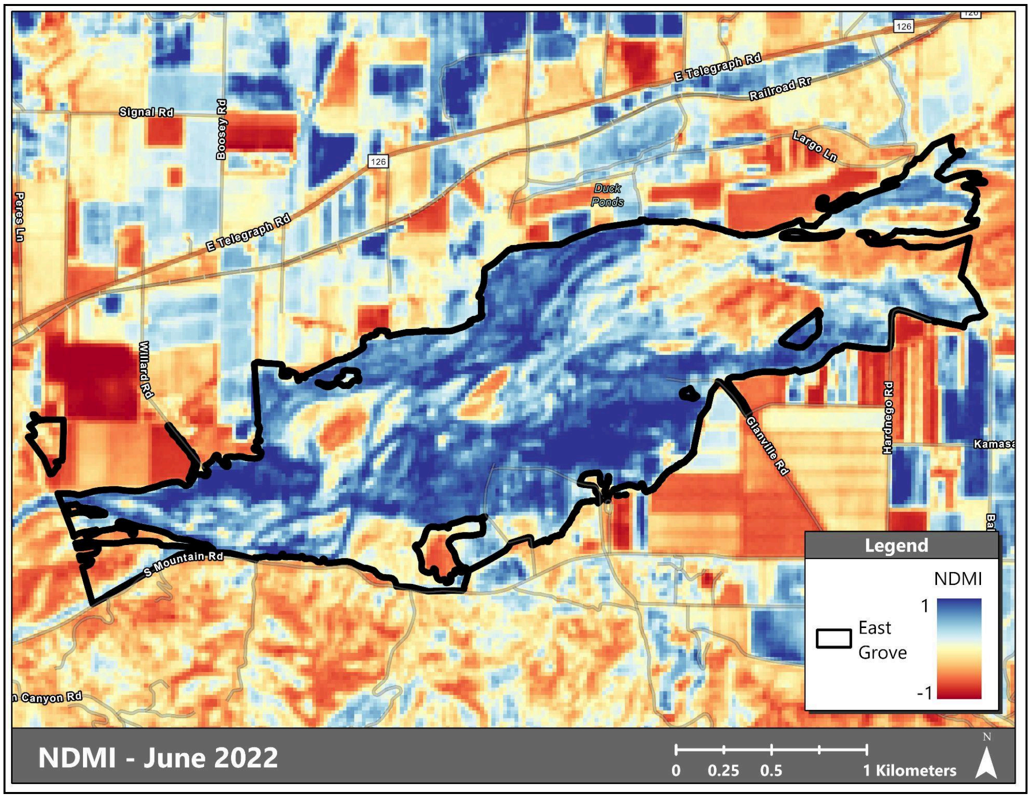
126
E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
Largo Ln
Duck Ponds
Peres Ln
E Telegraph Rd
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
n Canyon Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2017
0 0.25 0.5 1 Kilometers
N

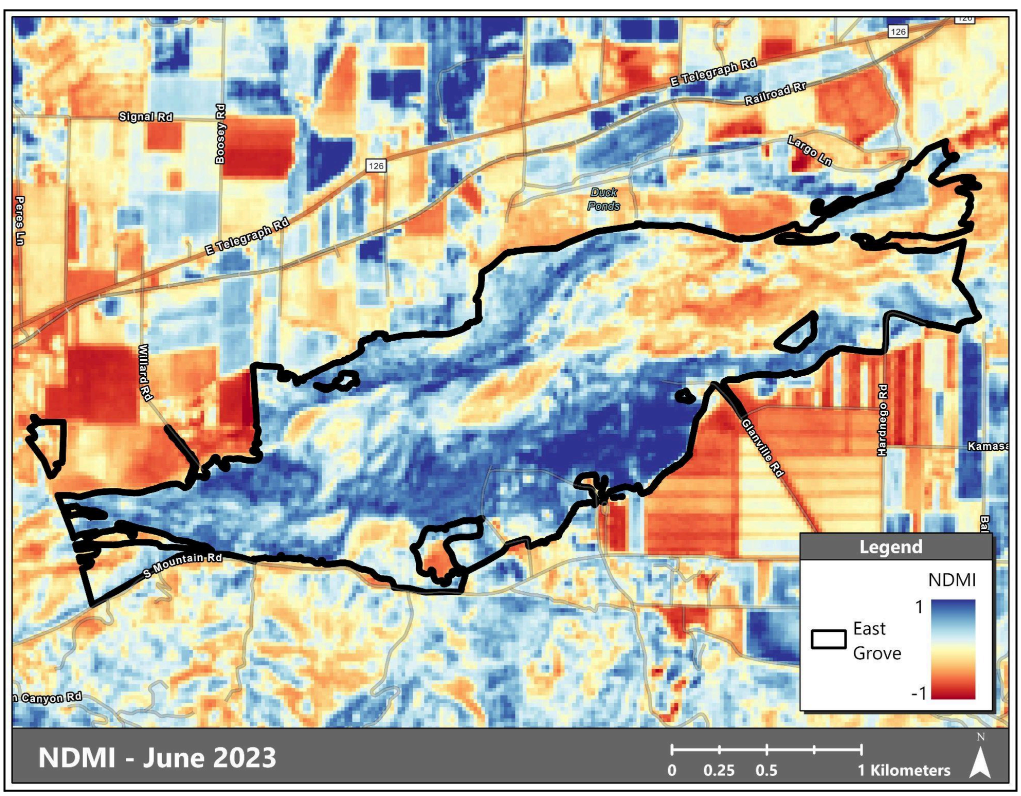

E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
126
Largo Ln
Duck Ponds
Peres Ln
E Telegraph Rd
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
n Canyon Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2018
0 0.25 0.5 1 Kilometers
N


E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
126
Largo Ln
Duck Ponds
Peres Ln
E Telegraph Rd
Willard Rd
Glanville Rd
Hardnego Rd
Kamasa
S Mountain Rd
n Canyon Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2019
0 0.25 0.5 1 Kilometers
N


E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
Largo Ln
Duck Ponds
Peres Ln
Willard Rd
Glanville Rd
Hardnego Rd
S Mountain Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2020
0 0.25 0.5 1 Kilometers
N

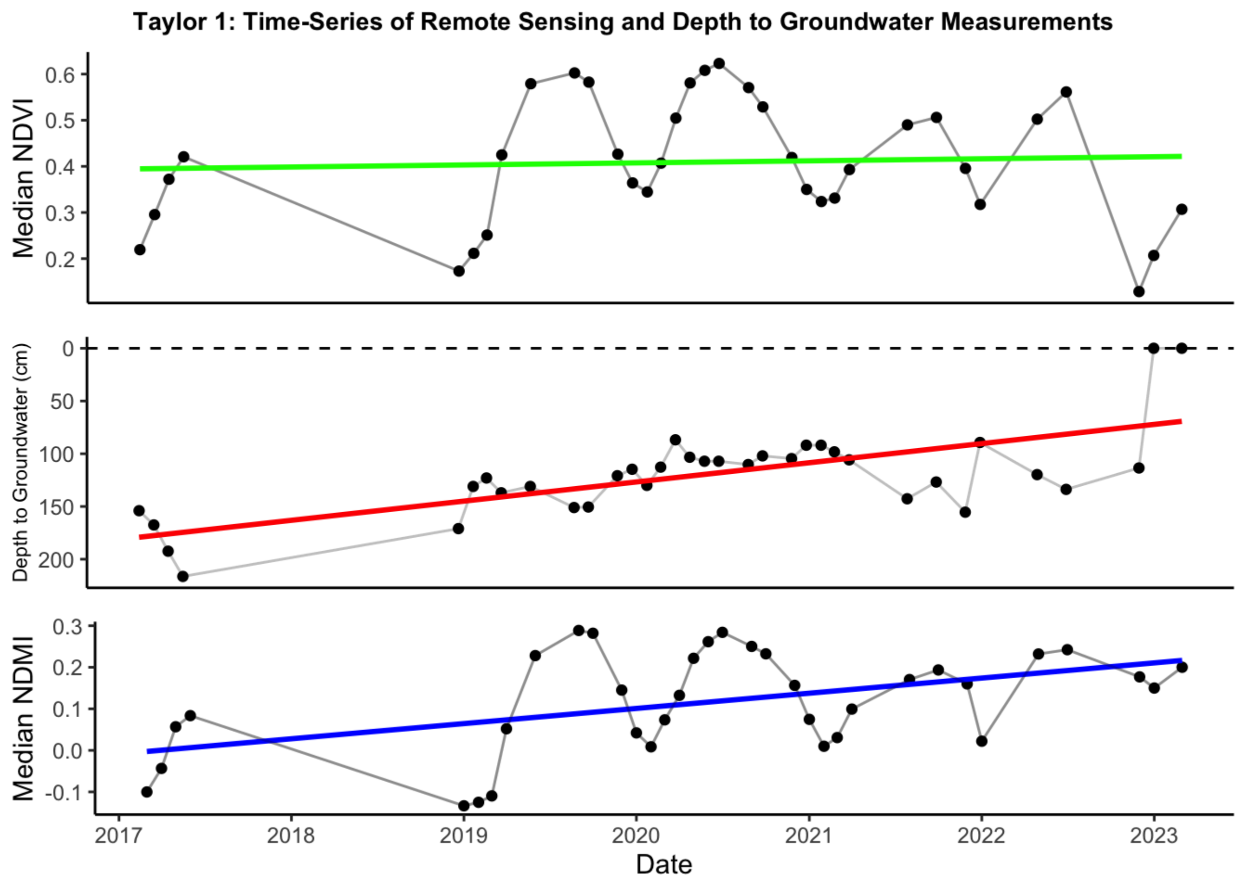

E Telegraph Rd
Railroad Rr
Signal Rd
Boosey Rd
Largo Ln
Duck Ponds
Peres Ln
Willard Rd
Glanville Rd
Hardnego Rd
S Mountain Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2021
0 0.25 0.5 1 Kilometers
N

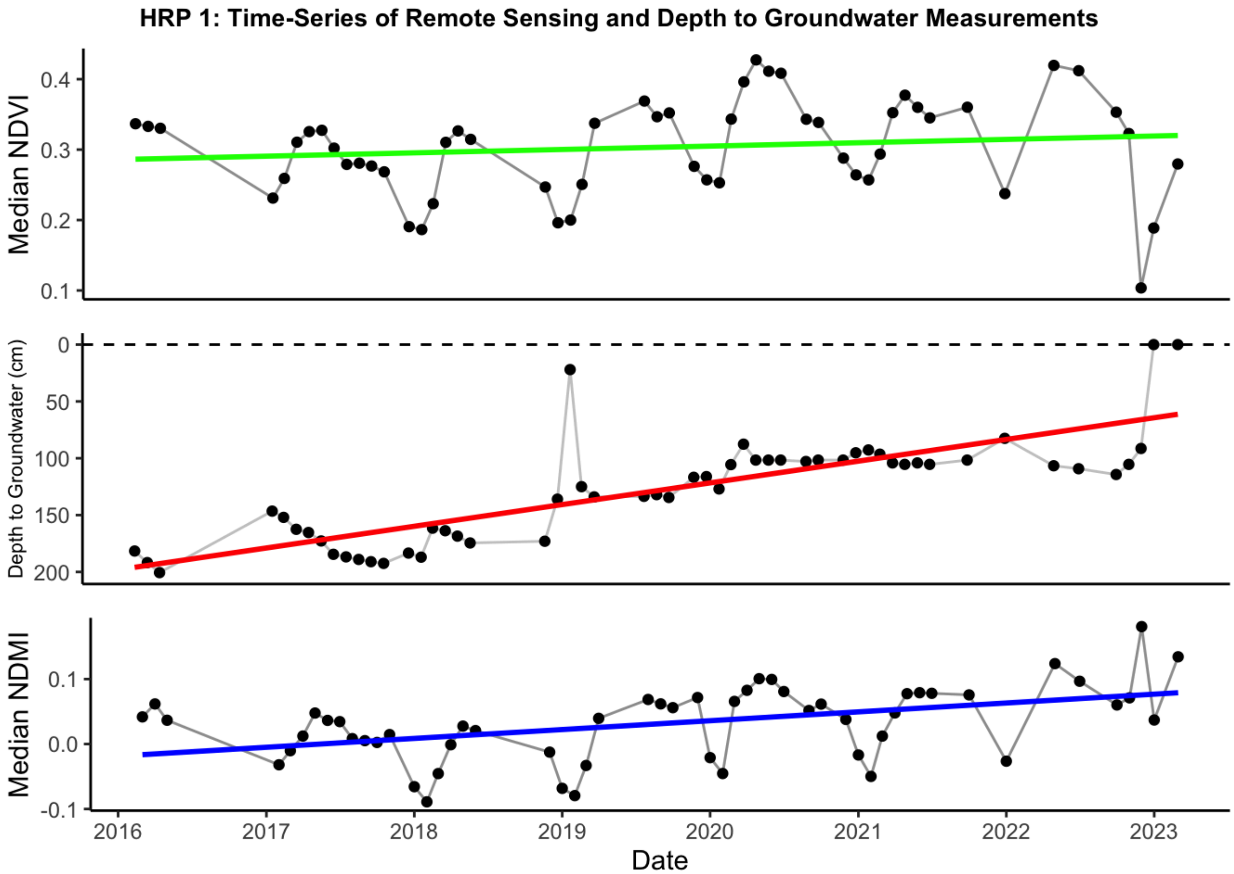

E Telegraph Rd
Railroad Rr
Largo Ln
Signal Rd
Boosey Rd
126
Peres Ln
Duck Ponds
Willard Rd
Glanville Rd
Hardnego Rd
S Mountain Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2022
0
0.25
0.5
1 Kilometers
N

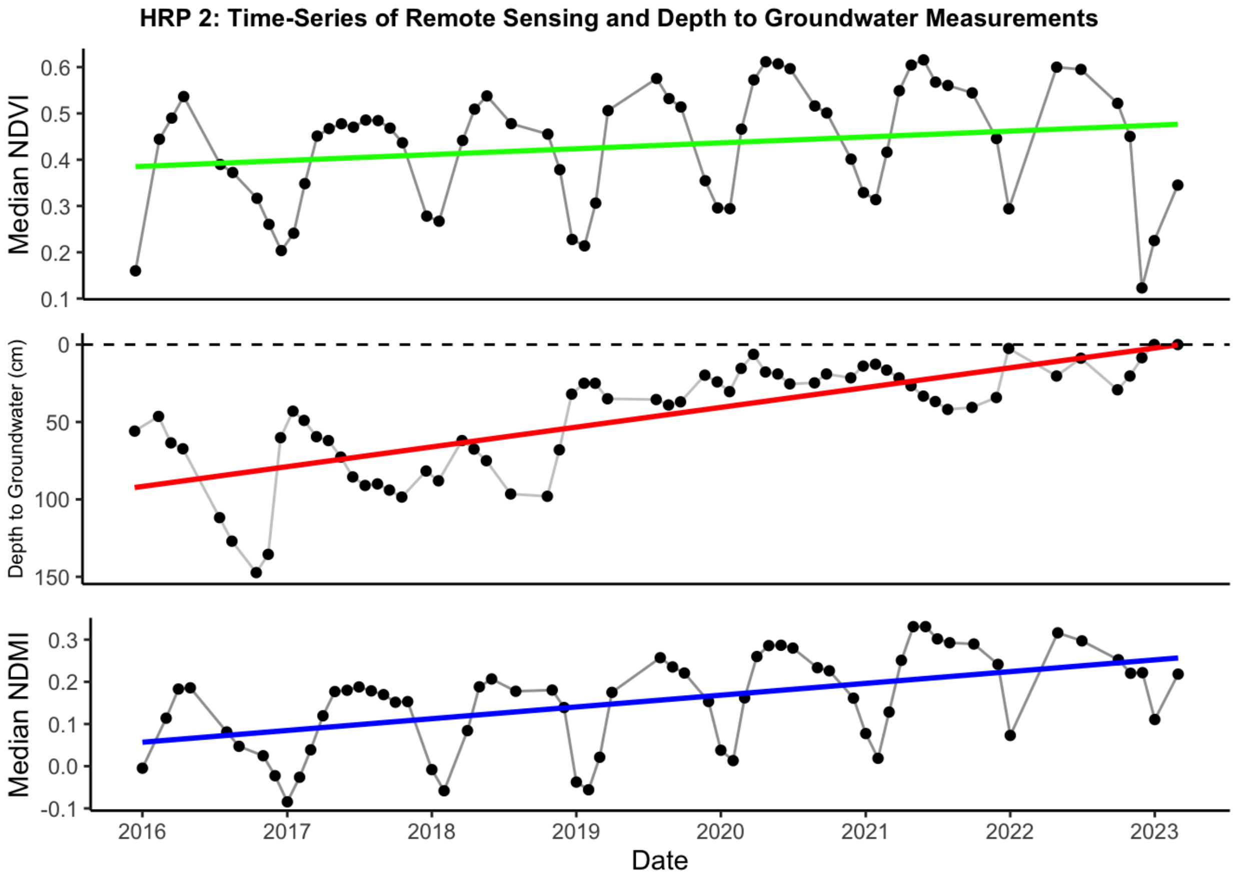

E Telegraph Rd
Railroad Rr
Largo Ln
Signal Rd
Boosey Rd
126
Peres Ln
Duck Ponds
Willard Rd
Glanville Rd
Hardnego Rd
S Mountain Rd
Legend
NDMI
1
-1
East Grove
NDMI - June 2023
0
0.25
0.5
1 Kilometers
N

3.3.2 NDVI/NDMI * Depth-to-Groundwater

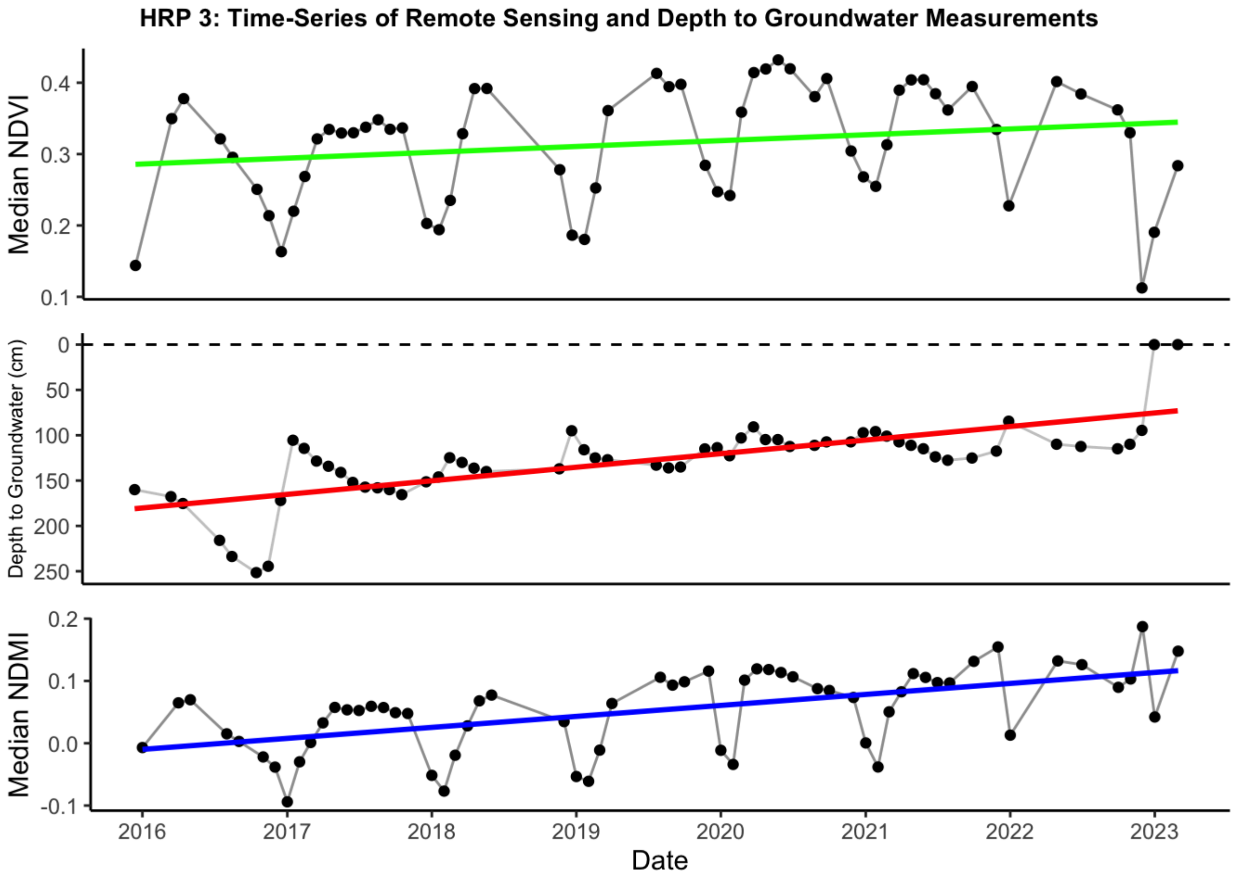
A. Time-Series

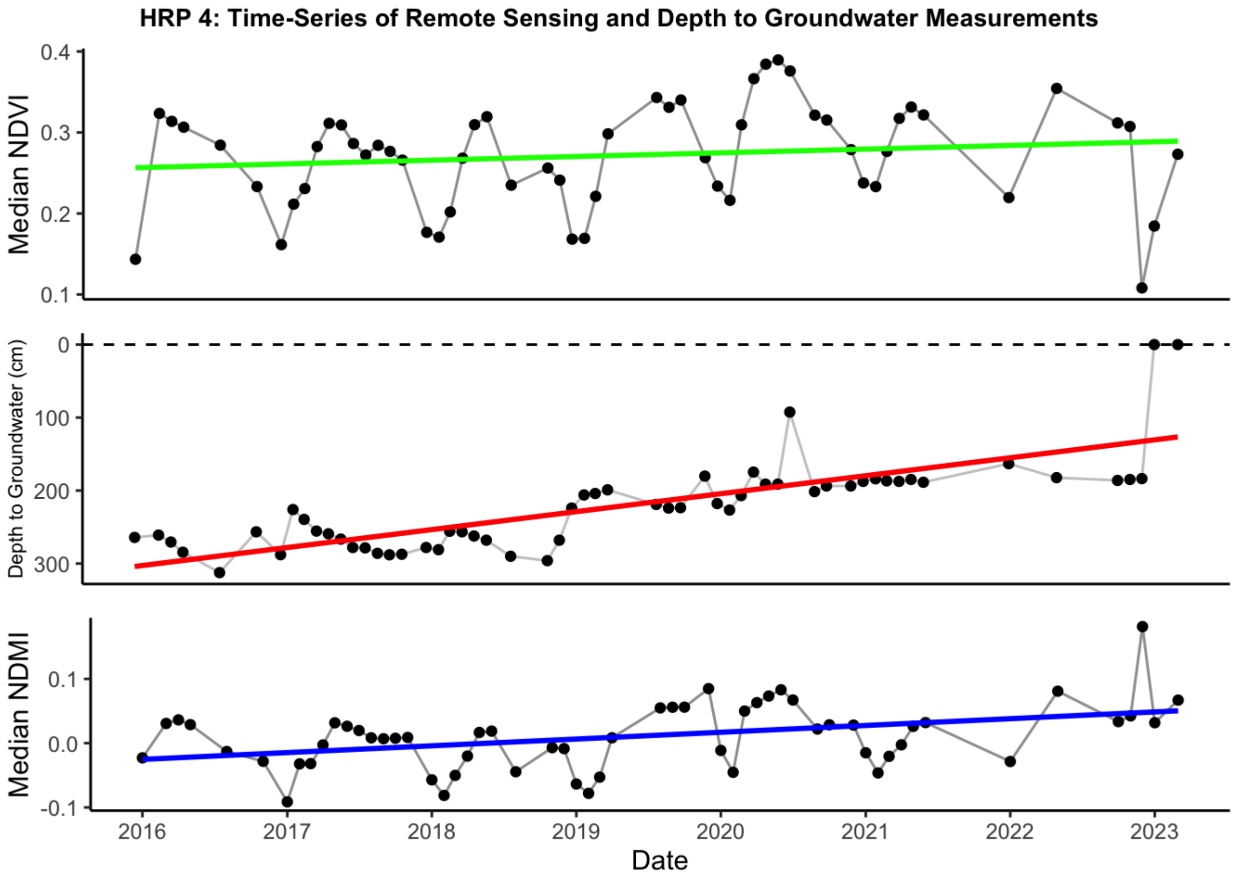


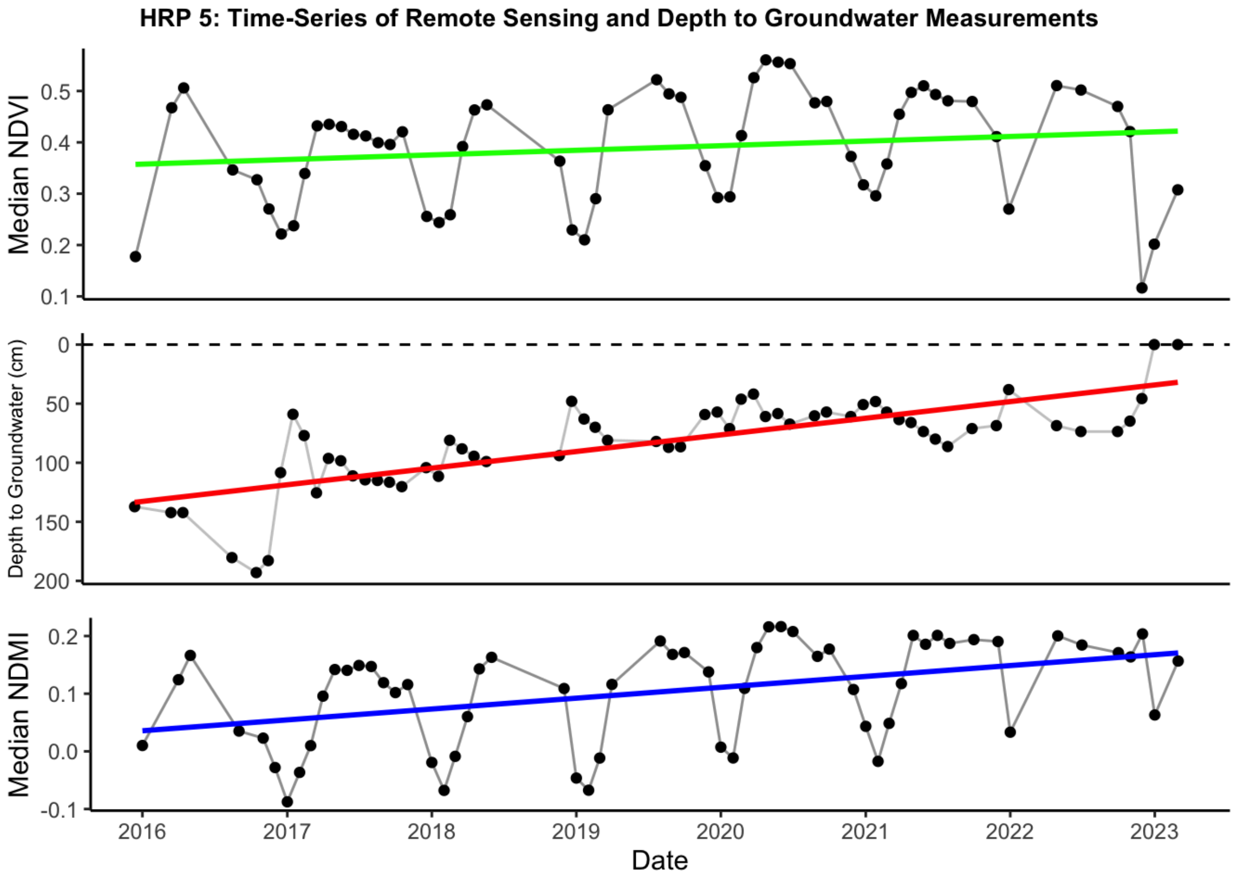

HRP 1: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
Median NDMI
0.1
0.0
-0.1
2016
2017
2018
2019
2020
2021
2022
2023
Date

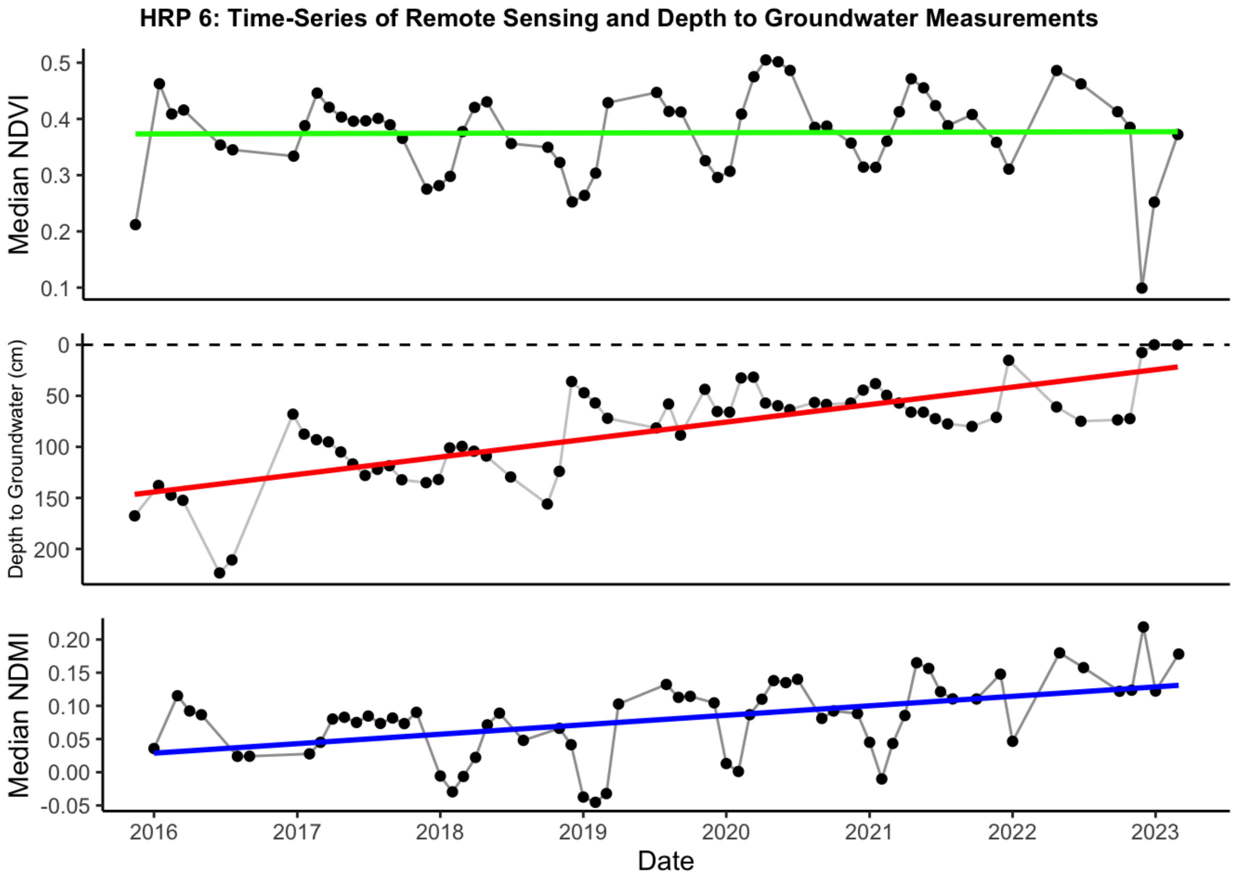


HRP 2: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
Median NDMI
0.3
0.2
0.1
0.0
-0.1
2016
2017
2018
2019
2020
2021
2022
2023
Date

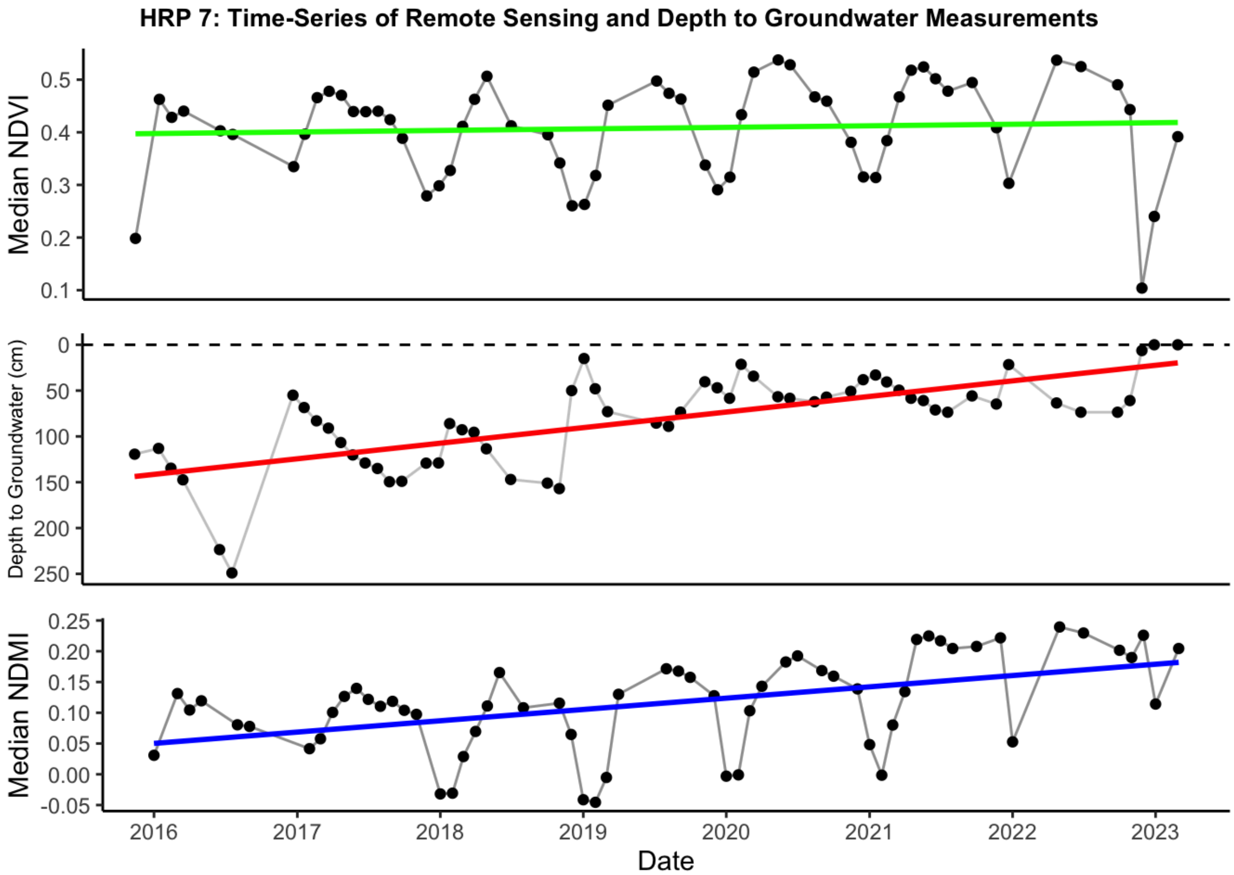

HRP 3: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
250
Median NDMI
0.2
0.1
0.0
-0.1
2016
2017
2018
2019
2020
2021
2022
2023
Date

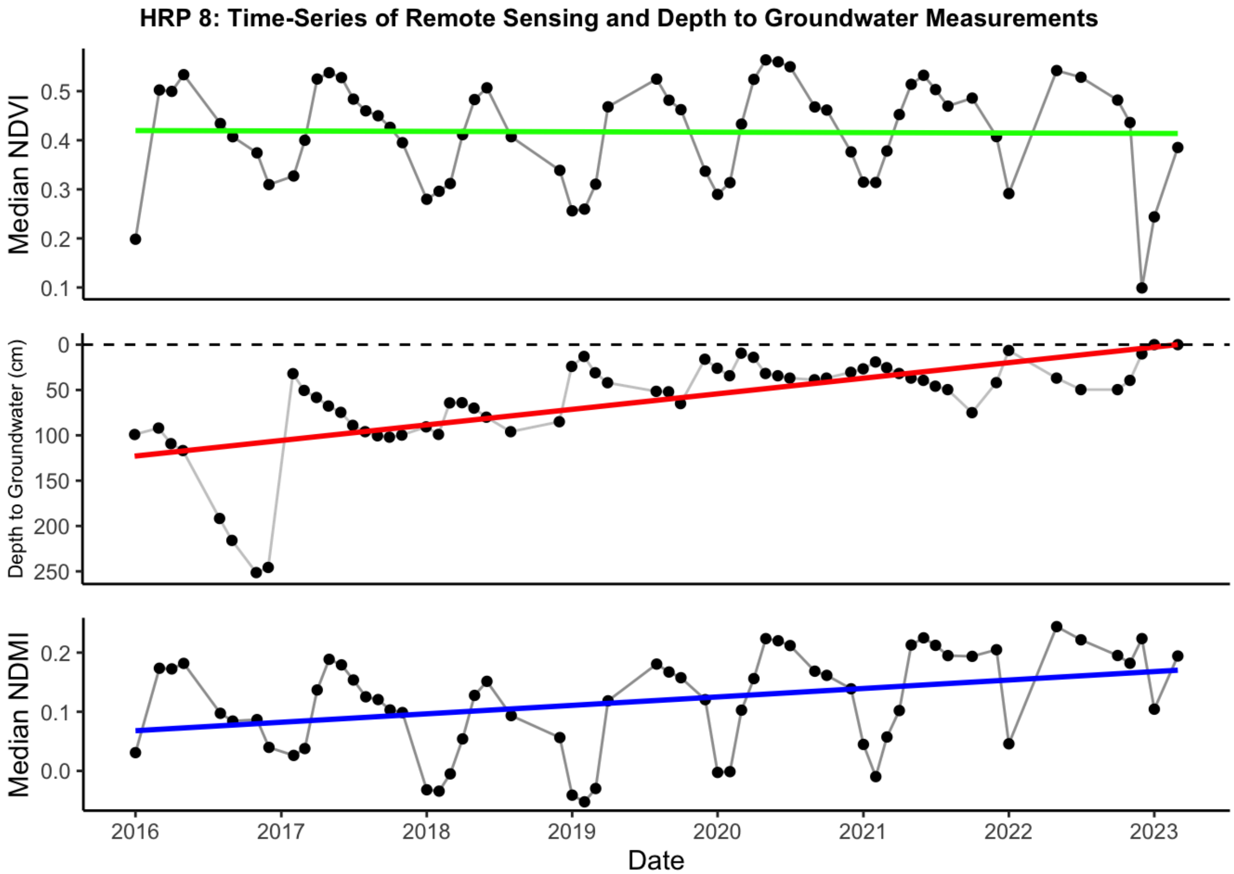

HRP 4: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
100
200
300
Median NDMI
0.1
0.0
-0.1
2016
2017
2018
2019
2020
2021
2022
2023
Date


HRP 5: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
Median NDMI
0.2
0.1
0.0
-0.1
2016
2017
2018
2019
2020
2021
2022
2023
Date

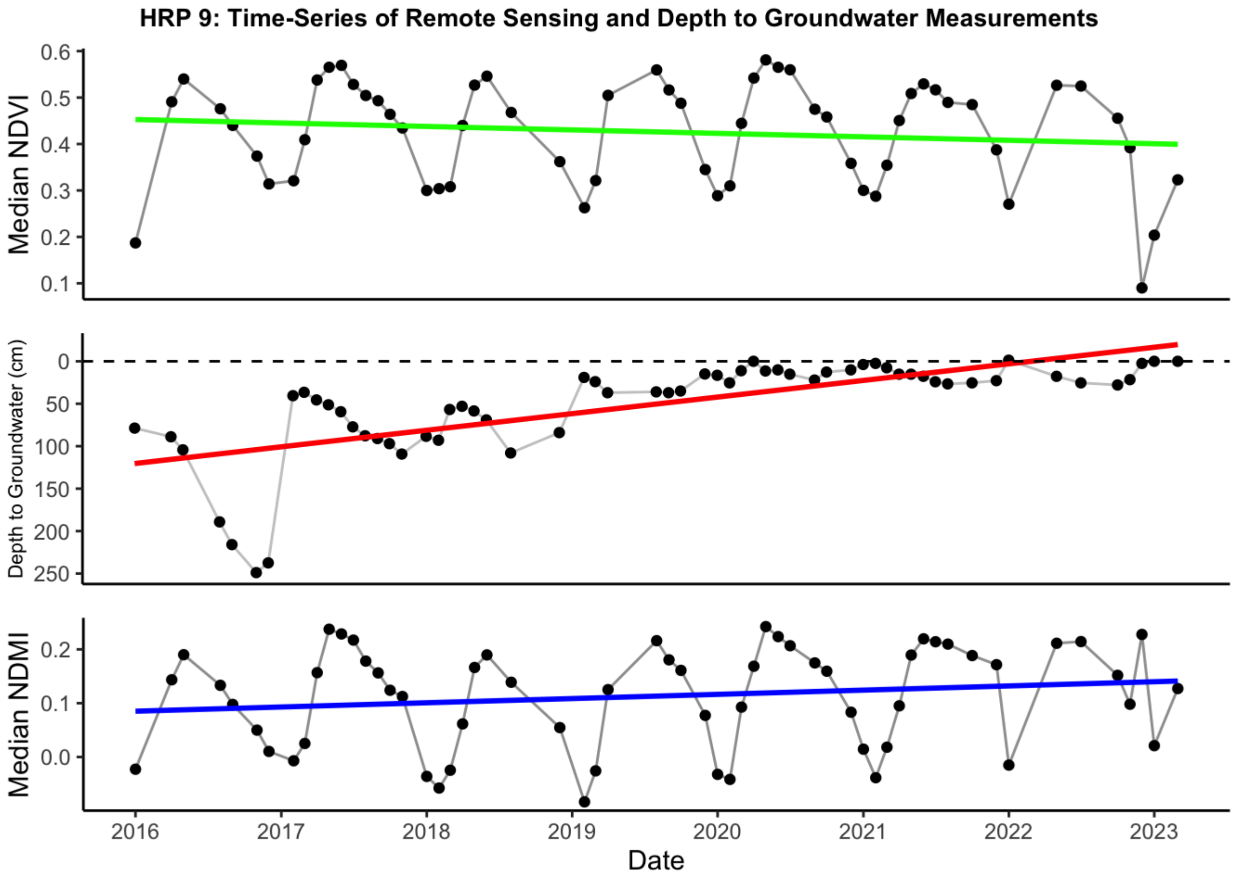


HRP 6: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
Median NDMI
0.20
0.15
0.10
0.05
0.00
-0.05
2016
2017
2018
2019
2020
2021
2022
2023
Date

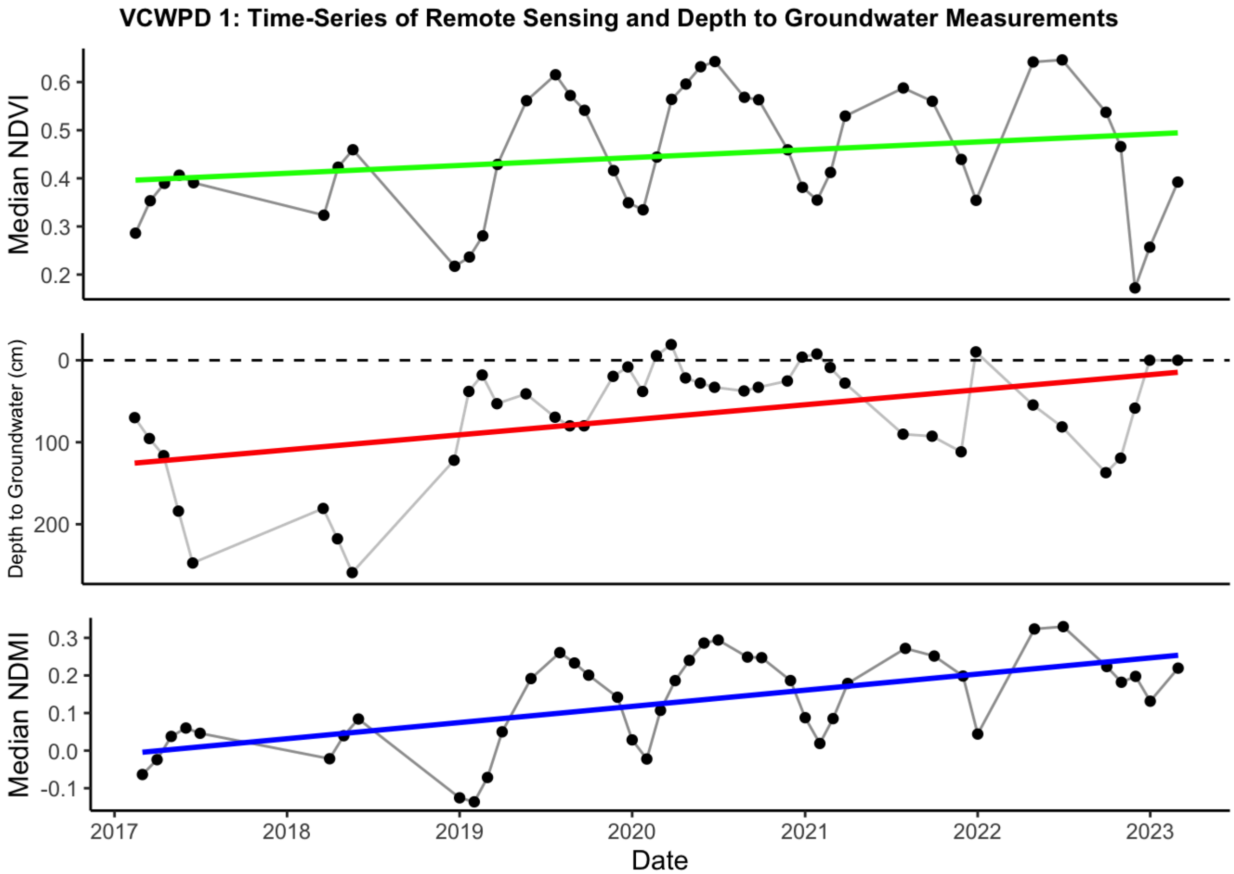

HRP 7: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
250
Median NDMI
0.25
0.20
0.15
0.10
0.05
0.00
-0.05
2016
2017
2018
2019
2020
2021
2022
2023
Date



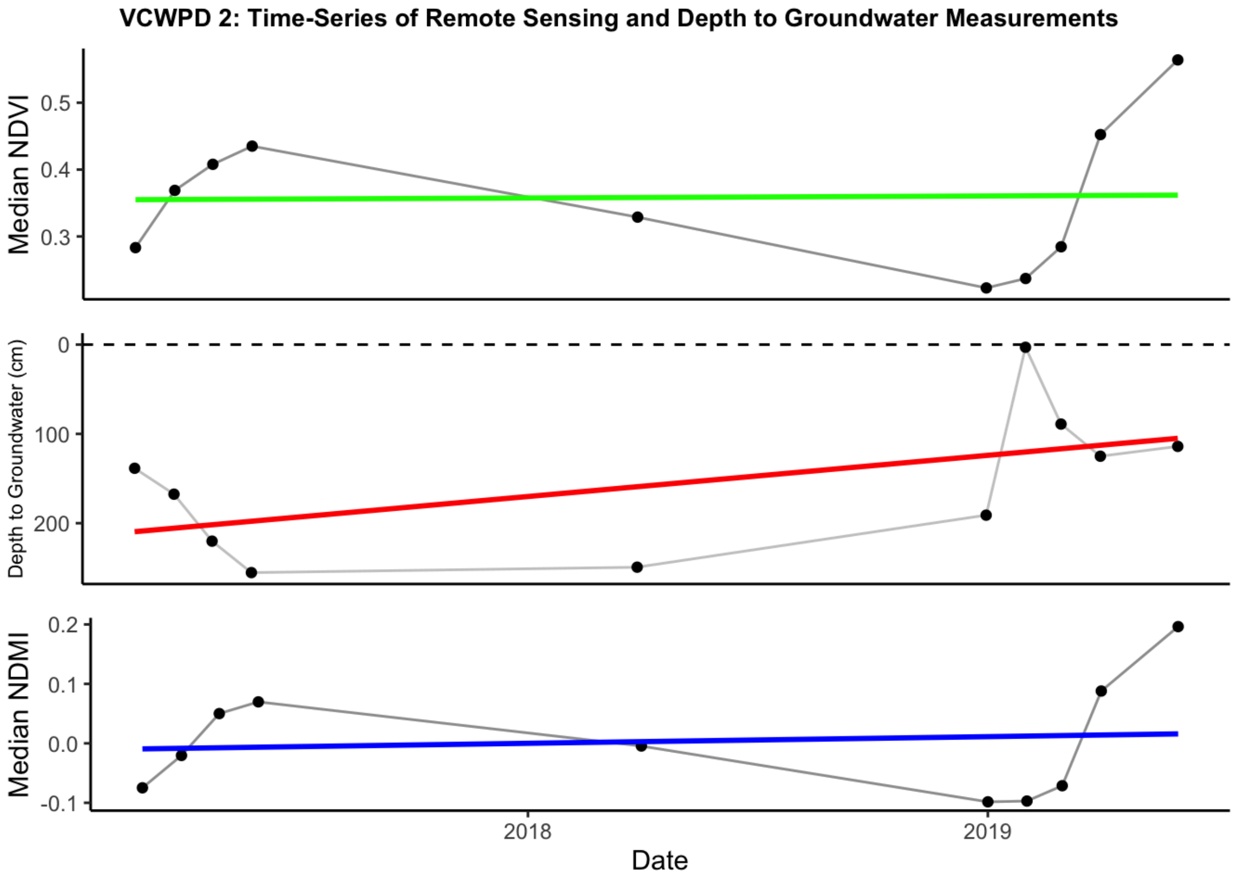
HRP 8: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
250
Median NDMI
0.2
0.1
0.0
2016
2017
2018
2019
2020
2021
2022
2023
Date



HRP 9: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
50
100
150
200
250
Median NDMI
0.2
0.1
0.0
2016
2017
2018
2019
2020
2021
2022
2023
Date

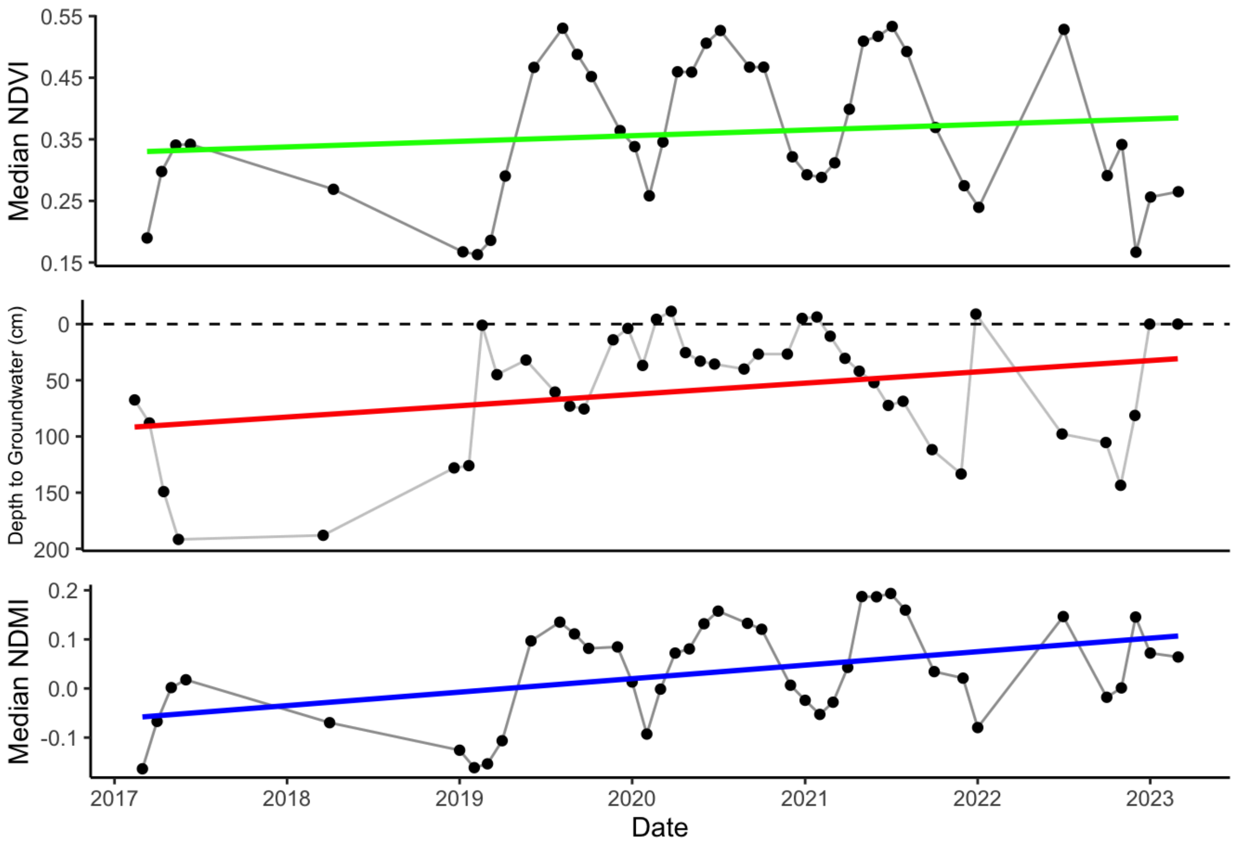


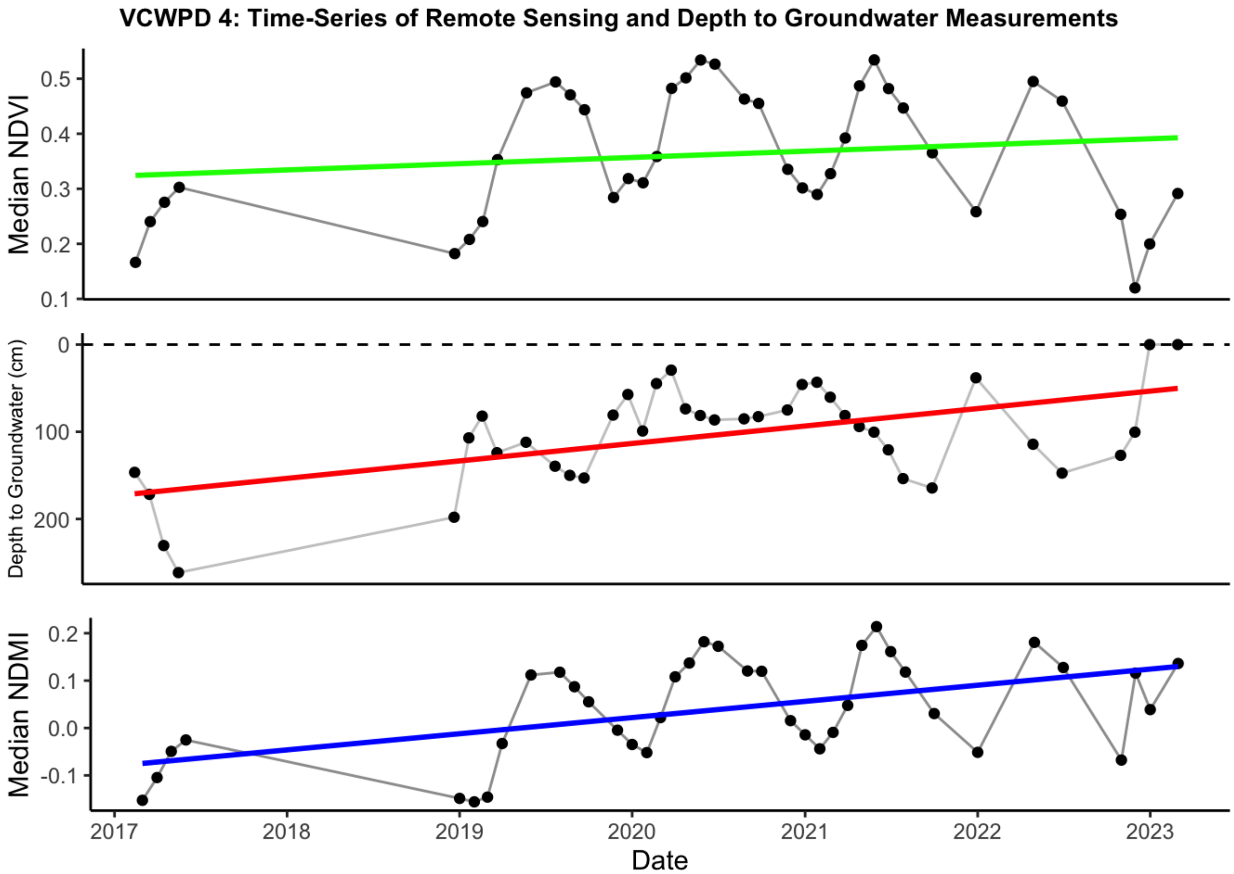
VCWPD 1: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
Depth to Groundwater (cm)
0
100
200
Median NDMI
0.3
0.2
0.1
0.0
-0.1
2017
2018
2019
2020
2021
2022
2023
Date



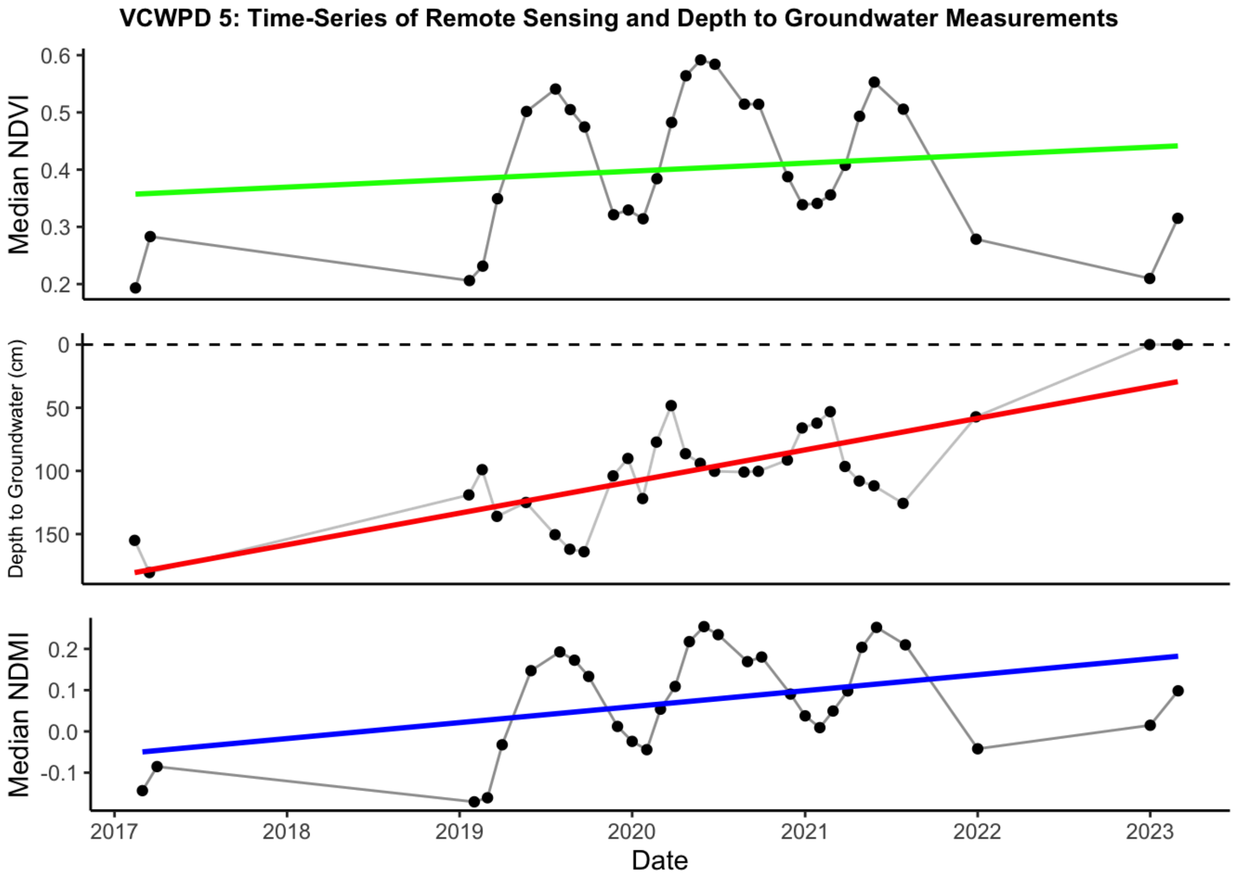
VCWPD 2: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.5
0.4
0.3
Depth to Groundwater (cm)
0
100
200
Median NDMI
0.2
0.1
0.0
-0.1
2018
2019
Date

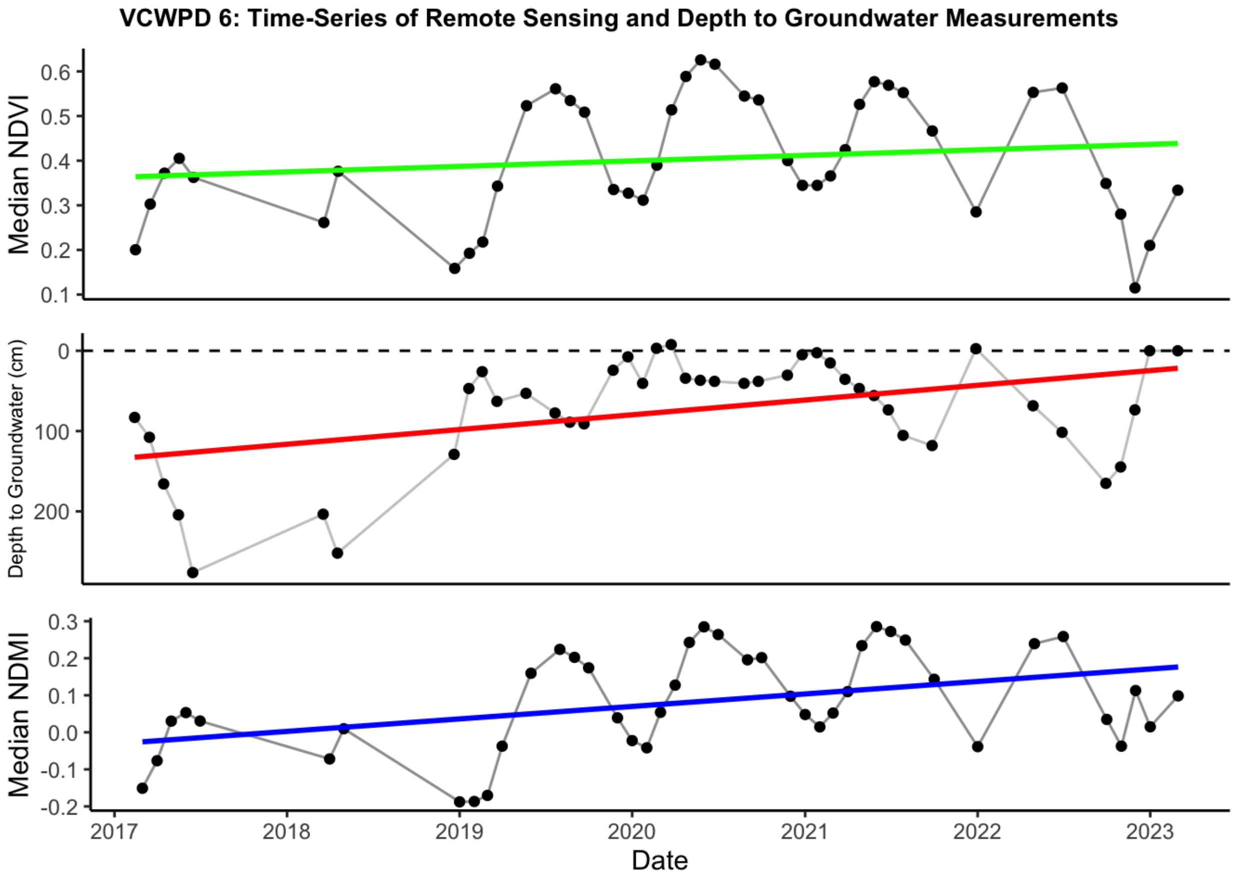
VCWPD 2: Time-Series of Remote Sensing and Depth to Groundwater Measurements

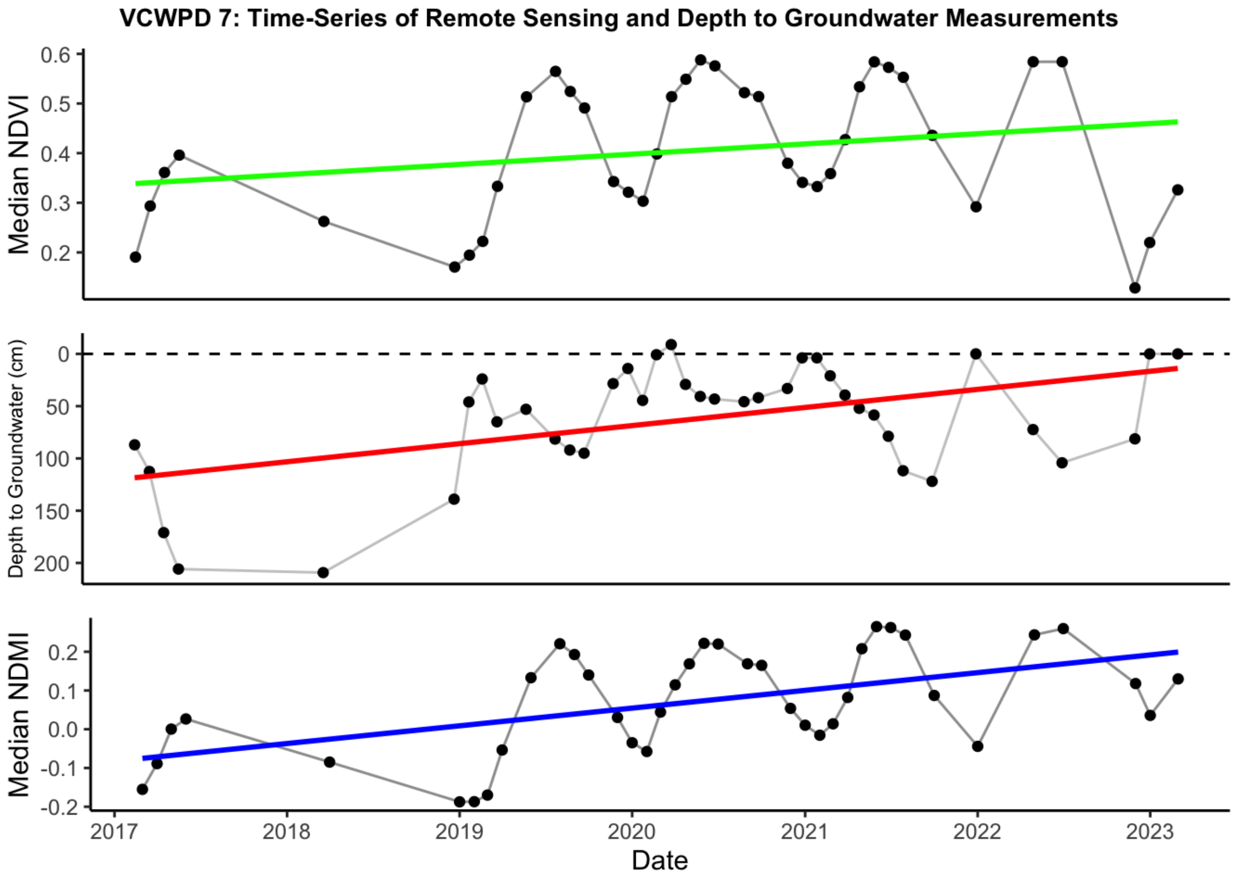


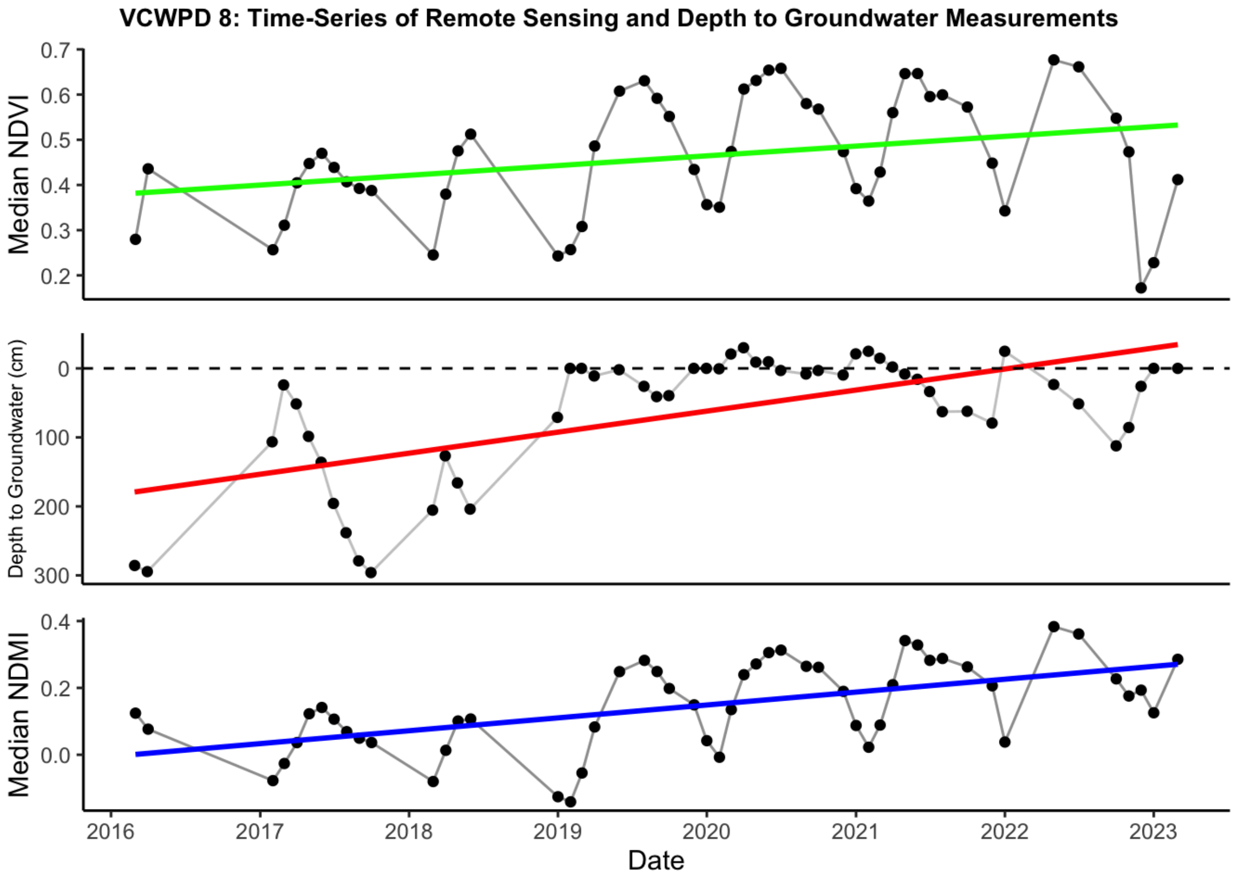


VCWPD 4: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
100
200
Median NDMI
0.2
0.1
0.0
-0.1
2017
2018
2019
2020
2021
2022
2023
Date

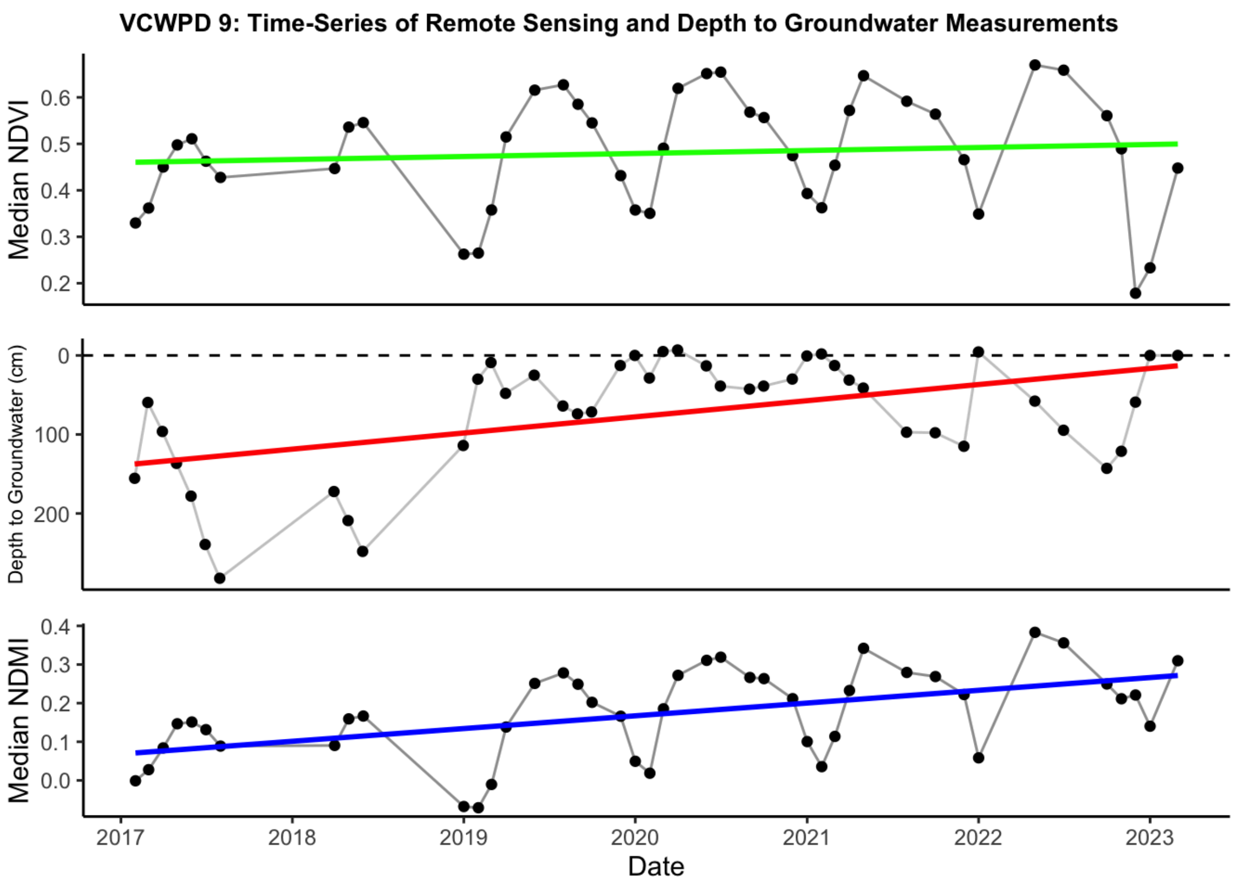

VCWPD 5: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
Depth to Groundwater (cm)
0
50
100
150
Median NDMI
0.2
0.1
0.0
-0.1
2017
2018
2019
2020
2021
2022
2023
Date


VCWPD 6: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
0.1
Depth to Groundwater (cm)
0
100
200
Median NDMI
0.3
0.2
0.1
0.0
-0.1
-0.2
2017
2018
2019
2020
2021
2022
2023
Date

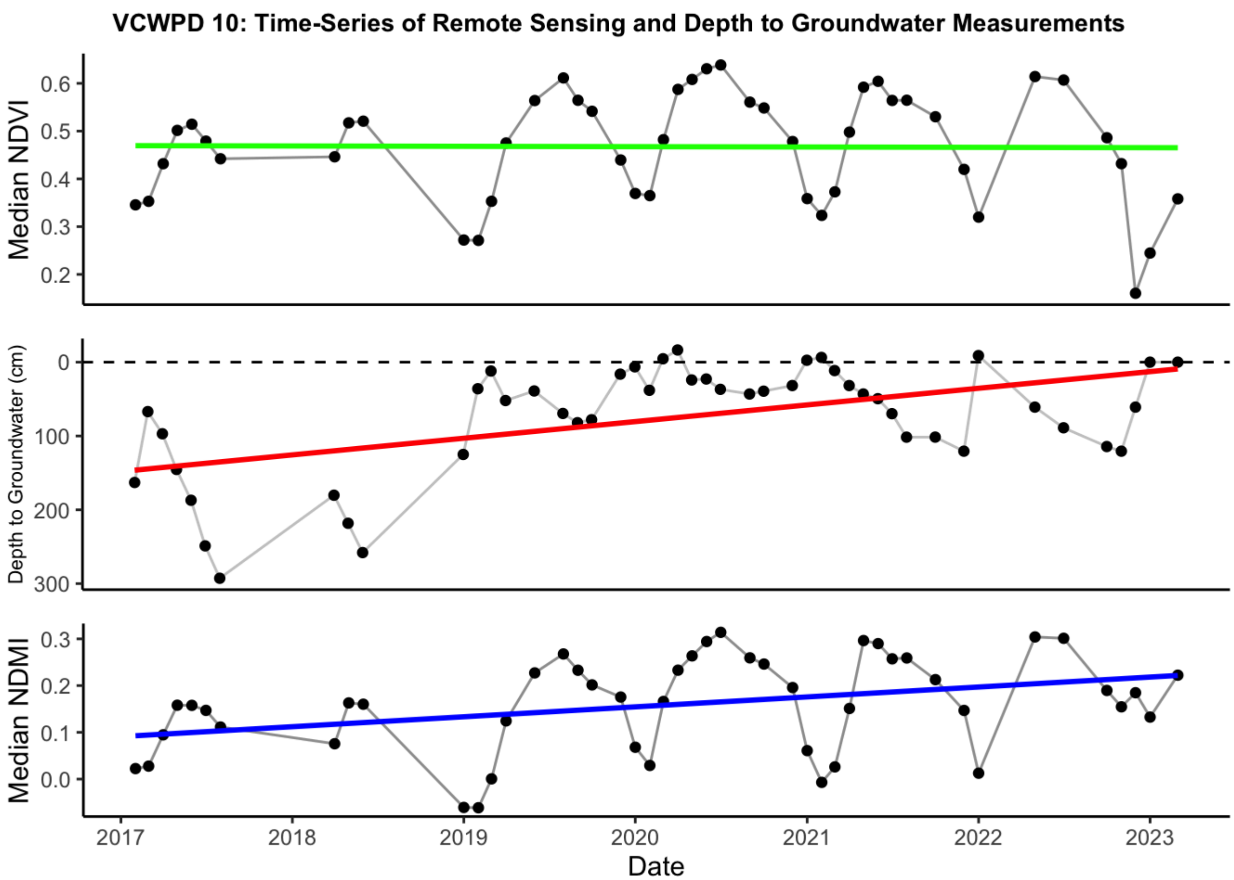

VCWPD 7: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
Depth to Groundwater (cm)
0
50
100
150
200
Median NDMI
0.2
0.1
0.0
-0.1
-0.2
2017
2018
2019
2020
2021
2022
2023
Date



VCWPD 8: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.7
0.6
0.5
0.4
0.3
0.2
Depth to Groundwater (cm)
0
100
200
300
Median NDMI
0.4
0.2
0.0
2016
2017
2018
2019
2020
2021
2022
2023
Date



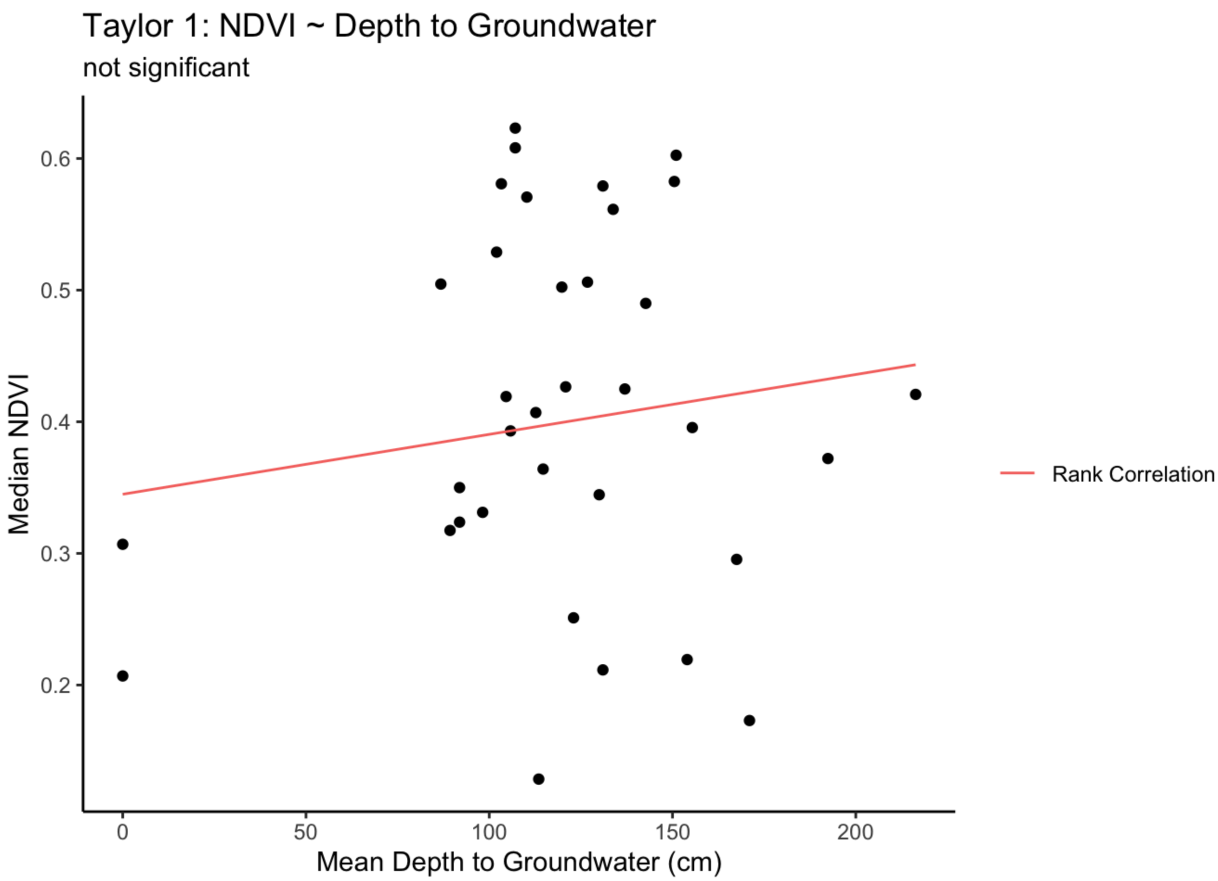
VCWPD 9: Time-Series of Remote Sensing and Depth to Groundwater Measurements
Median NDVI
0.6
0.5
0.4
0.3
0.2
Depth to Groundwater (cm)
0
100
200
Median NDMI
0.4
0.3
0.2
0.1
0.0
2017
2018
2019
2020
2021
2022
2023
Date



B. All Data

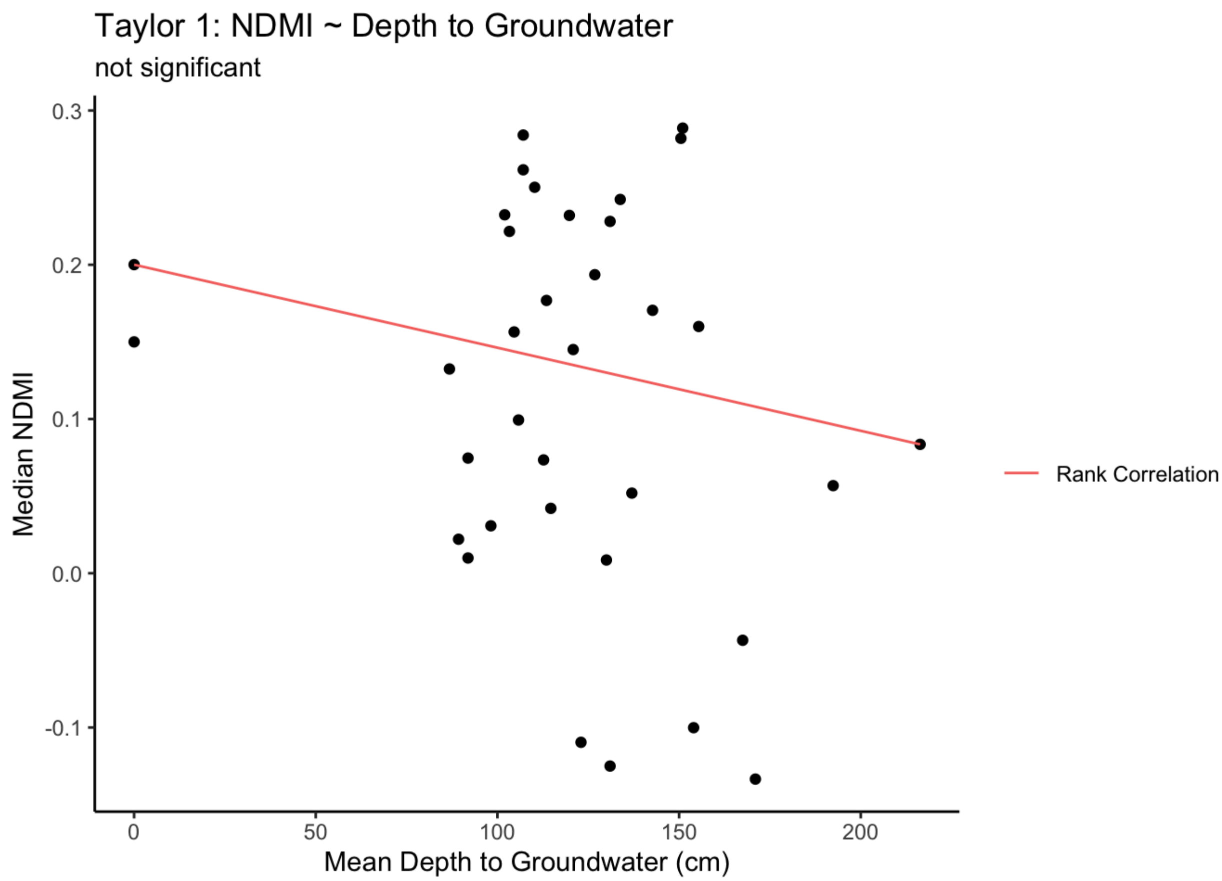
Taylor 1 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_taylor1)
##
## Coefficients:
##              Estimate Std. Error t.value  p.value
## (Intercept) 0.34494107 0.08326582  4.1426 0.000224 ***
## mean_dtg    0.00045481 0.00059501  0.7644 0.450079
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.01899854
## Reduction in Dispersion Test: 0.63909 p-value: 0.42976
```



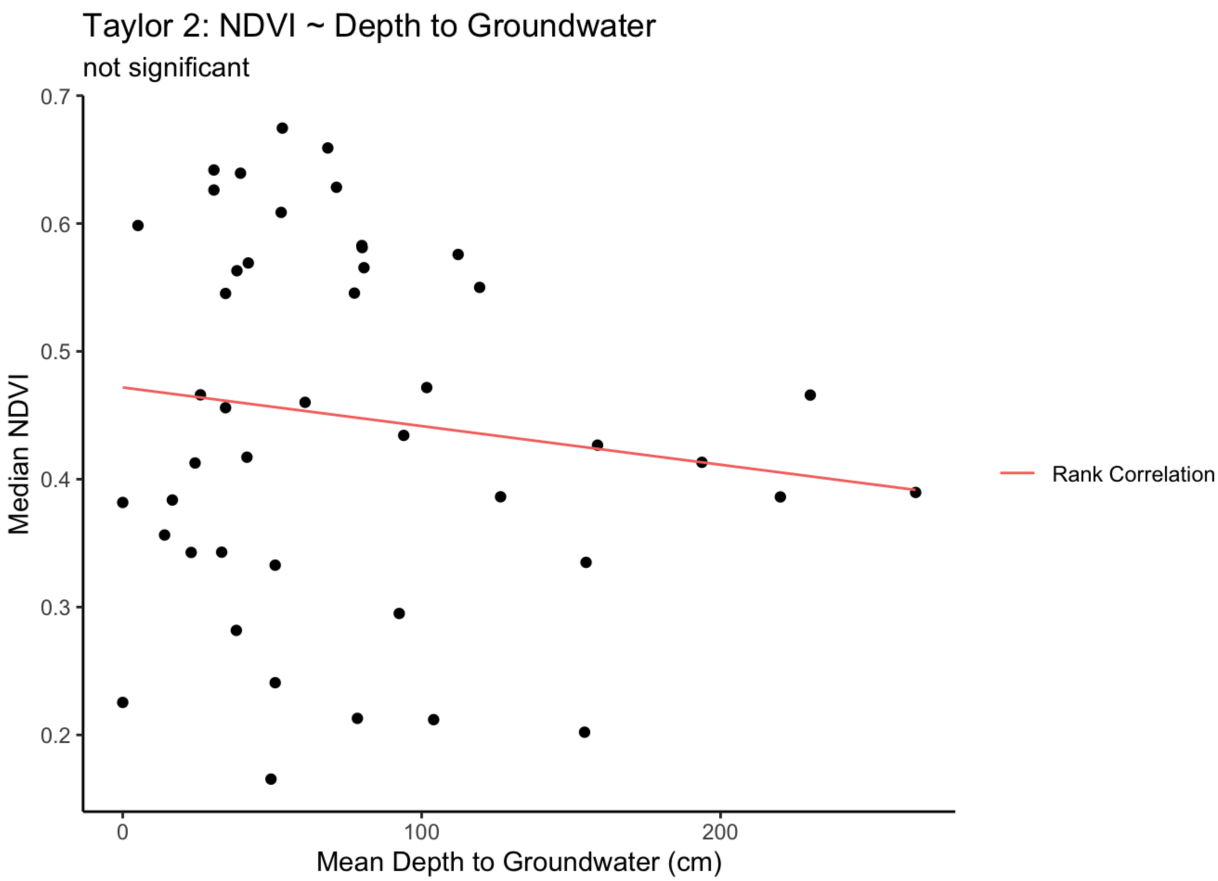
Taylor 1 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_taylor1)
##
## Coefficients:
##               Estimate  Std. Error t.value p.value
## (Intercept)  0.20008954  0.07611275  2.6289 0.01291 *
## mean_dtg    -0.00053863  0.00057471 -0.9372 0.35546
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.02978721
## Reduction in Dispersion Test: 1.01316 p-value: 0.32147
```



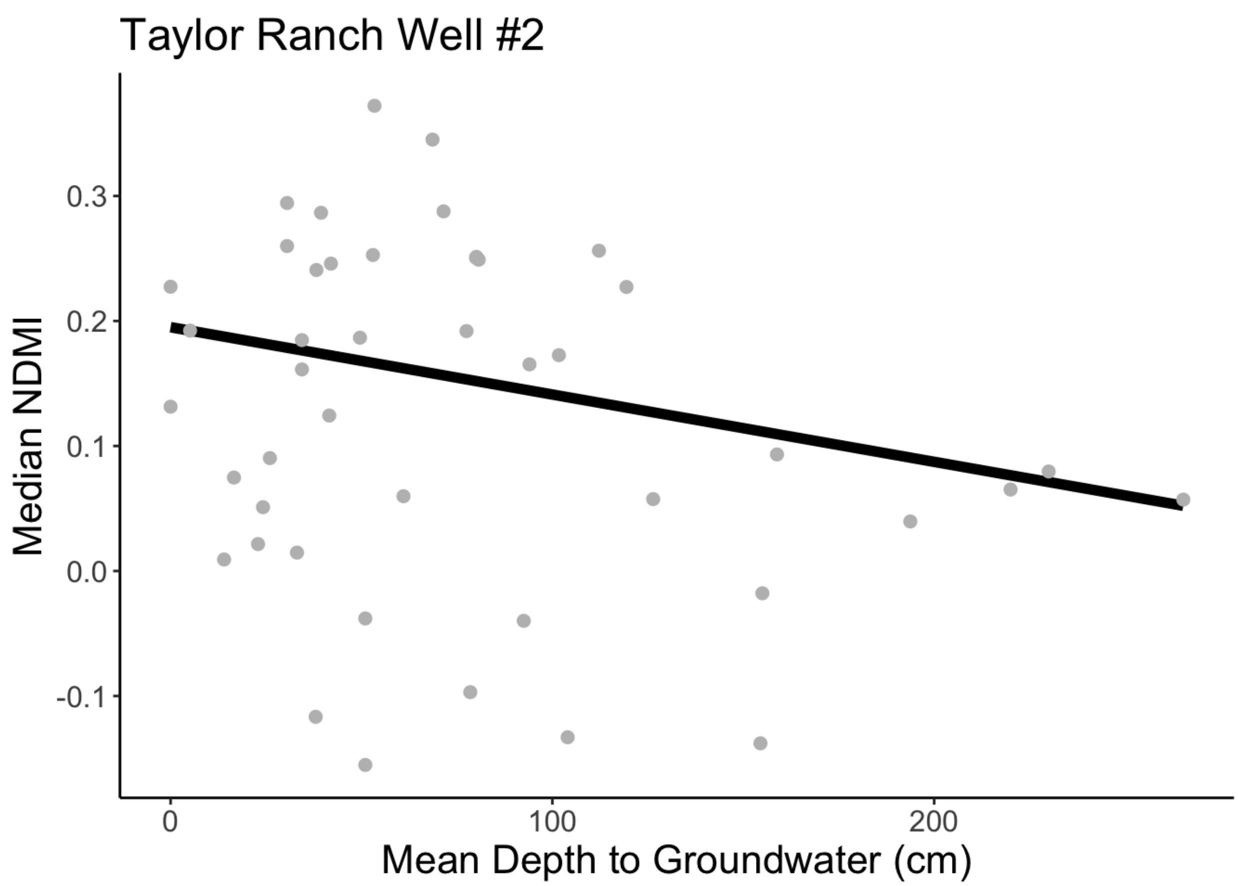
Taylor 2 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_taylor2)
##
## Coefficients:
##                Estimate  Std. Error t.value  p.value
## (Intercept)  0.47178576  0.04833421  9.7609 1.79e-12 ***
## mean_dtg    -0.00030225  0.00036580 -0.8263   0.4132
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.01459905
## Reduction in Dispersion Test: 0.63706 p-value: 0.42916
```



Taylor 2 NDMI

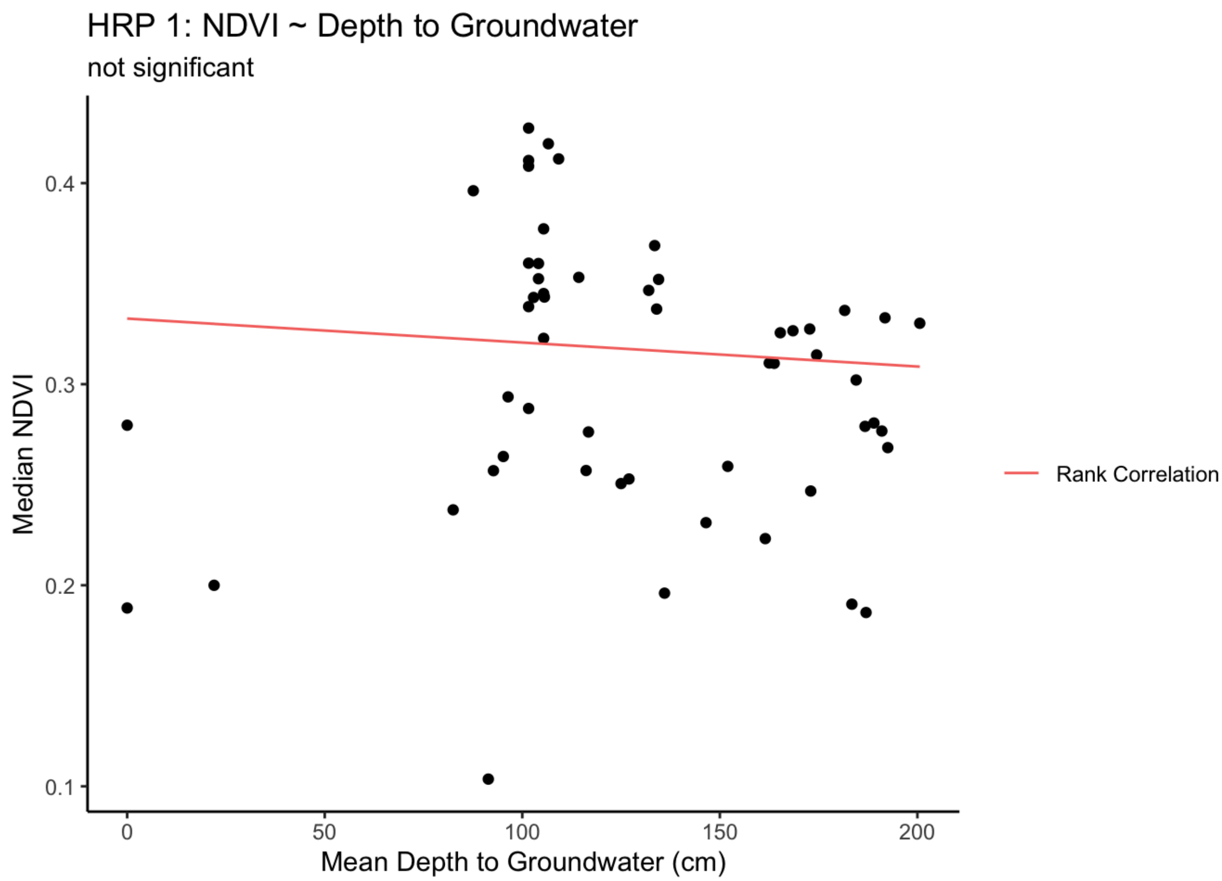
```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_taylor2)
##
## Coefficients:
##                Estimate  Std. Error t.value  p.value
## (Intercept)  0.19501889  0.03775538  5.1653 5.88e-06 ***
## mean_dtg    -0.00053847  0.00034530 -1.5594   0.1262
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.05319175
## Reduction in Dispersion Test: 2.41574 p-value: 0.12745
```




```
Unset
## [1] -0.1551258
```

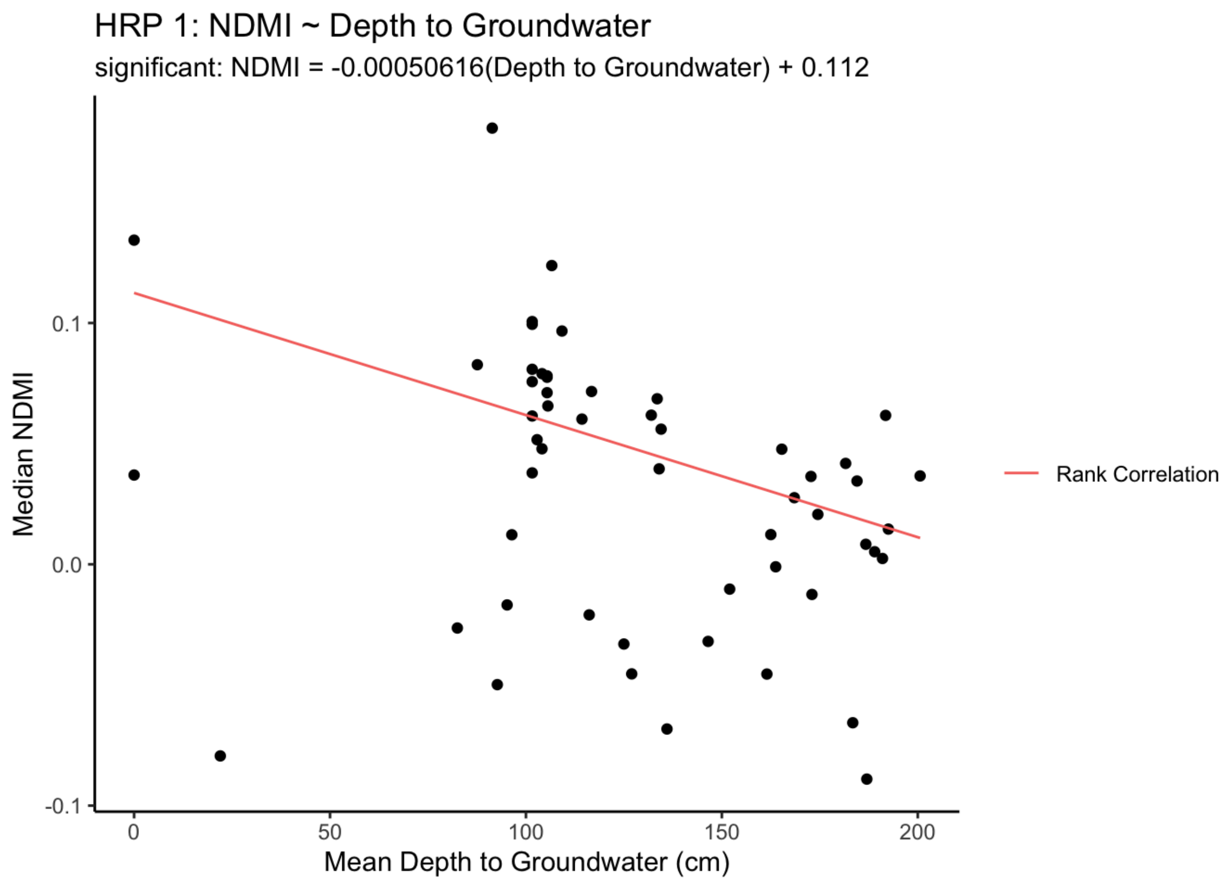
HRP 1 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp1)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.33264445  0.02905243 11.4498 7.899e-16 ***
## mean_dtg    -0.00011928  0.00019694 -0.6057    0.5474
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.00597395
## Reduction in Dispersion Test: 0.31251 p-value: 0.57854
```



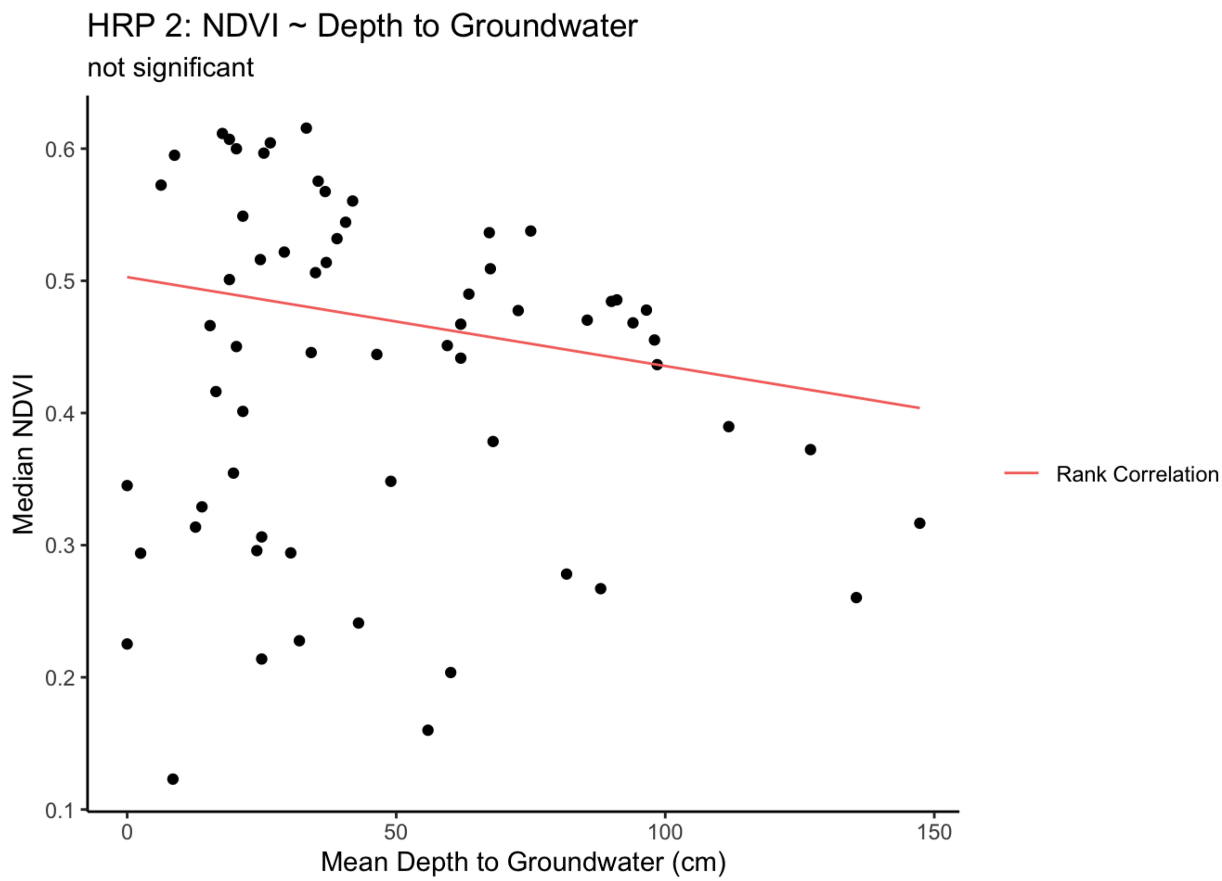
HRP 1 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp1)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.11245256  0.01777001  6.3282 5.815e-08 ***
## mean_dtg    -0.00050616  0.00012622 -4.0101 0.0001948 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.1774028
## Reduction in Dispersion Test: 11.21442 p-value: 0.00152
```



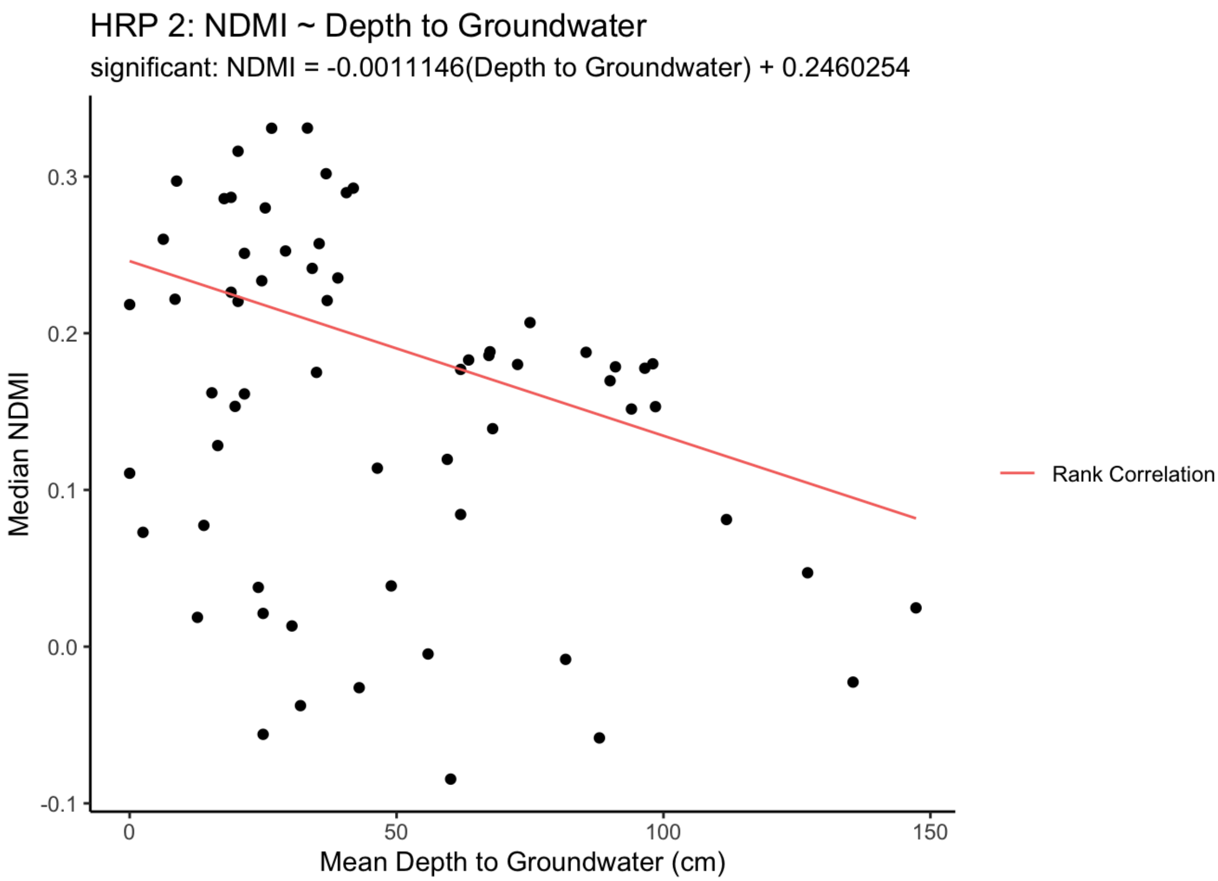
HRP 2 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp2)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  0.50281272  0.02832403 17.7522  <2e-16 ***
## mean_dtg    -0.00067262  0.00042726 -1.5743  0.1206
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0314022
## Reduction in Dispersion Test: 1.97764 p-value: 0.16471
```



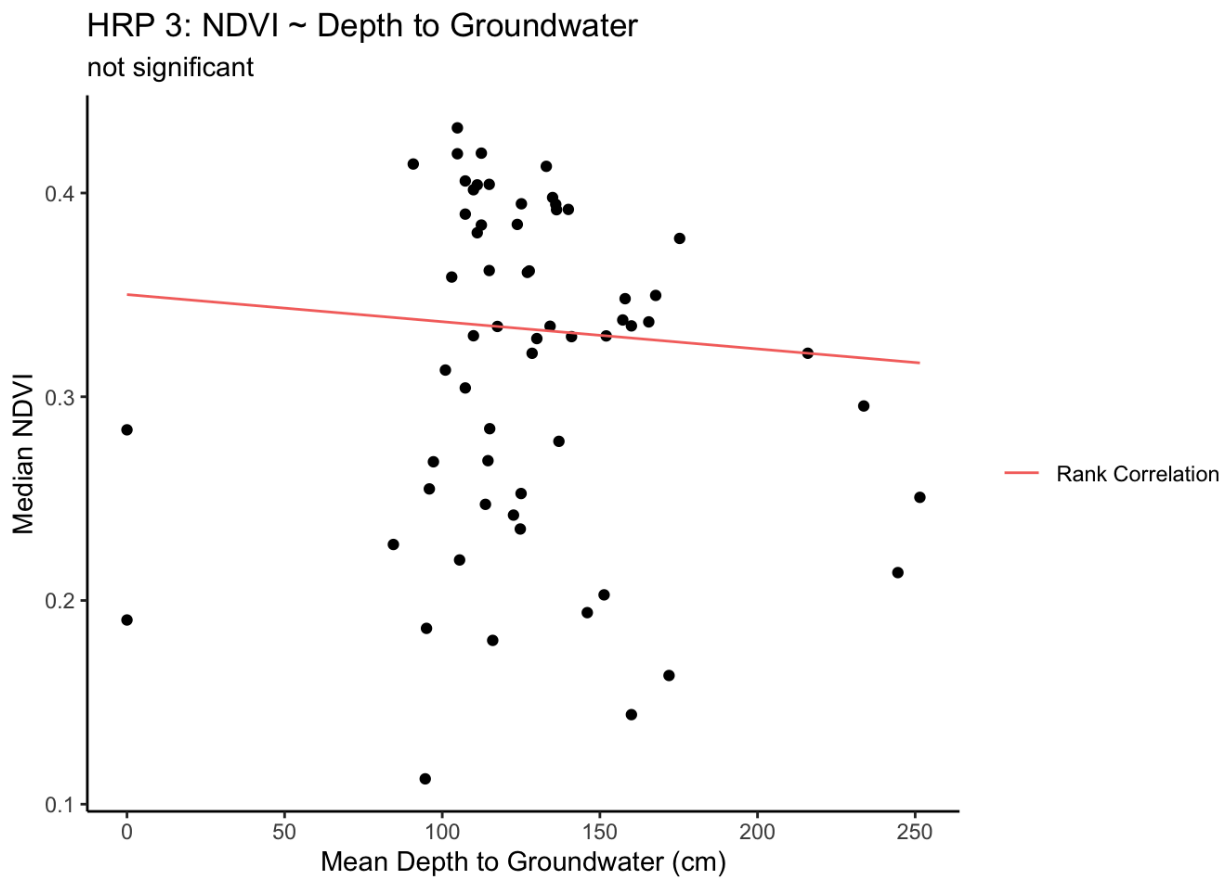
HRP 2 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp2)
##
## Coefficients:
##              Estimate Std. Error t.value   p.value
## (Intercept)  0.2460254  0.0253858  9.6915 5.831e-14 ***
## mean_dtg    -0.0011146  0.0003418 -3.2609   0.00182 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.141729
## Reduction in Dispersion Test: 10.07312 p-value: 0.00236
```



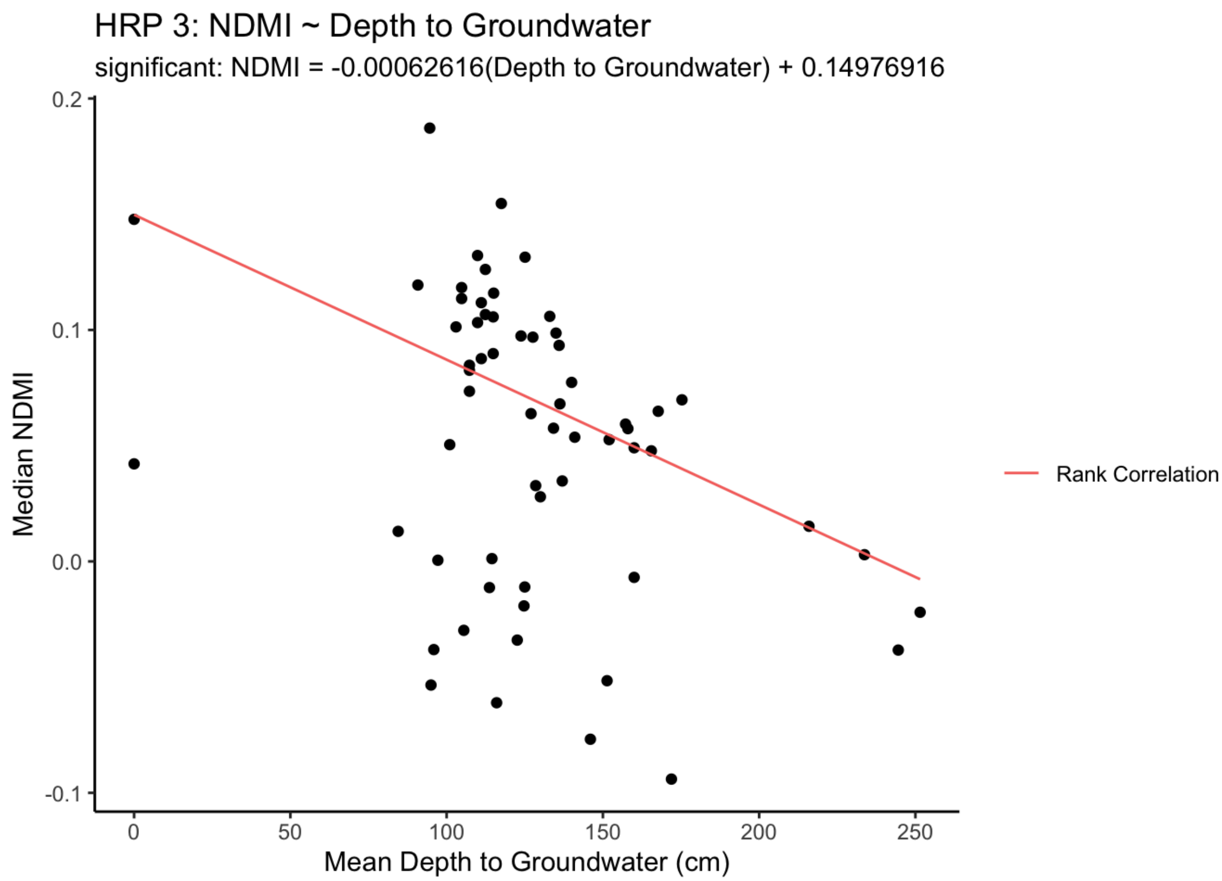
HRP 3 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp3)
##
## Coefficients:
##                Estimate  Std. Error t.value   p.value
## (Intercept)  0.35018688  0.03321372 10.5434 3.412e-15 ***
## mean_dtg    -0.00013353  0.00023491 -0.5684    0.5719
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.00541207
## Reduction in Dispersion Test: 0.32105 p-value: 0.57313
```



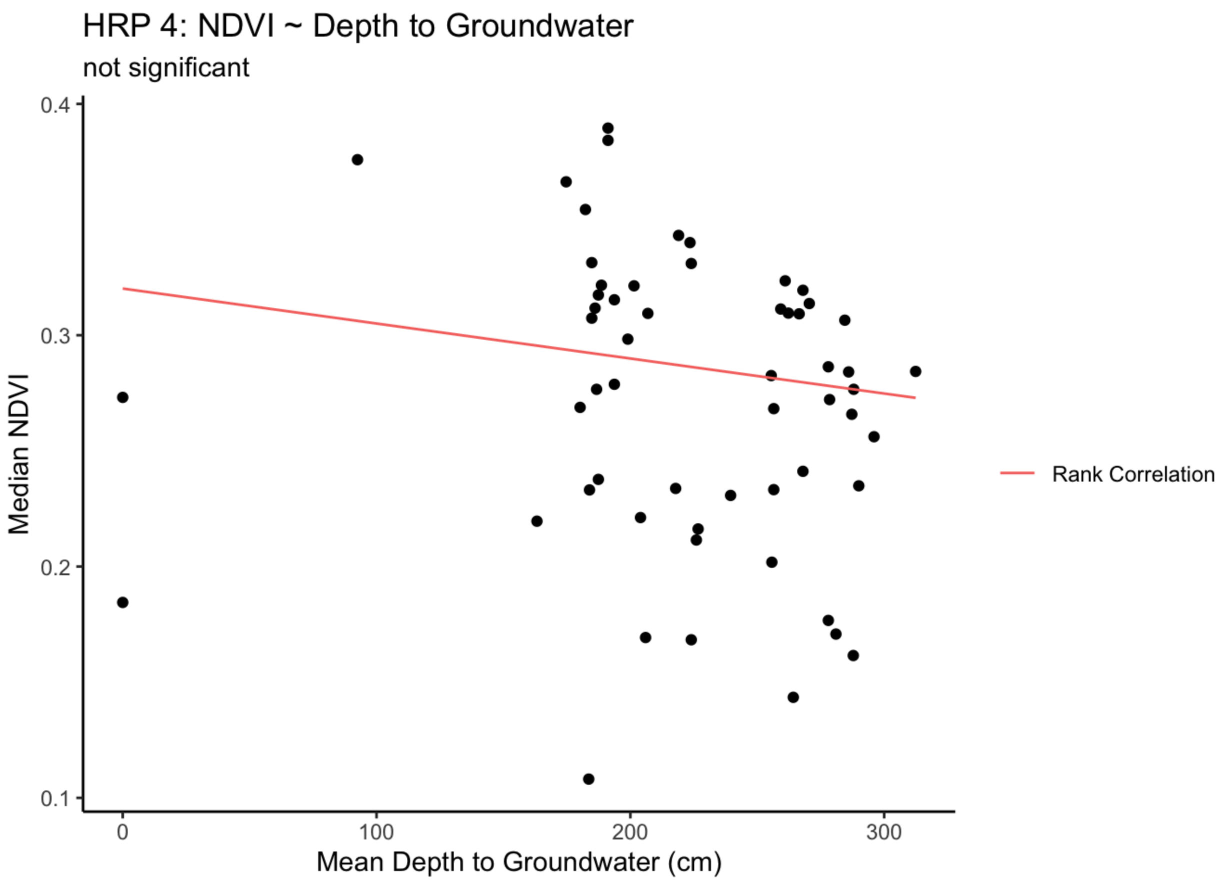
HRP 3 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp3)
##
## Coefficients:
##                Estimate  Std. Error t.value   p.value
## (Intercept)  0.14976916  0.01976010  7.5794 2.821e-10 ***
## mean_dtg    -0.00062616  0.00014823 -4.2241 8.423e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.1915458
## Reduction in Dispersion Test: 13.97878 p-value: 0.00042
```



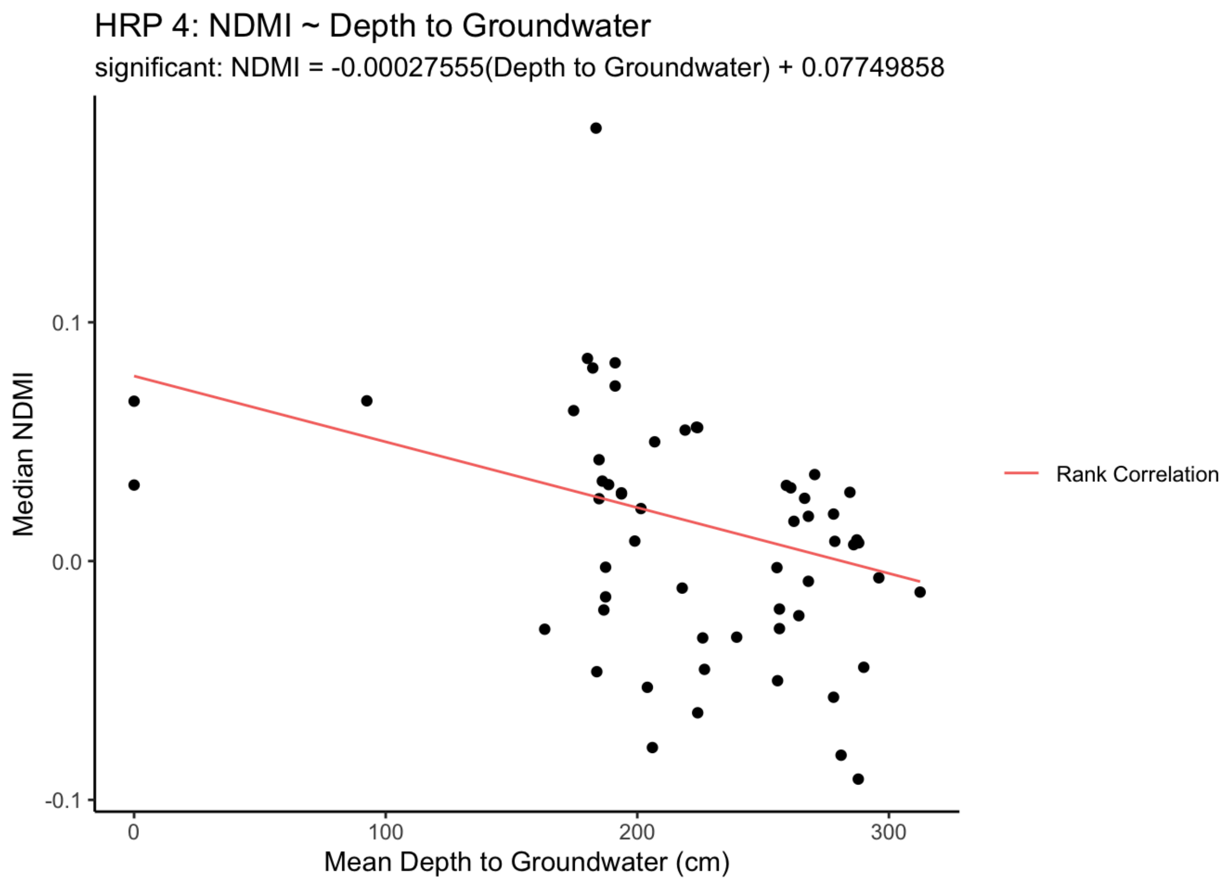
HRP 4 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp4)
##
## Coefficients:
##                Estimate  Std. Error t.value   p.value
## (Intercept)  0.32020333  0.03410283  9.3893 5.074e-13 ***
## mean_dtg    -0.00015133  0.00013699 -1.1047    0.2741
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.01614741
## Reduction in Dispersion Test: 0.90268 p-value: 0.34622
```



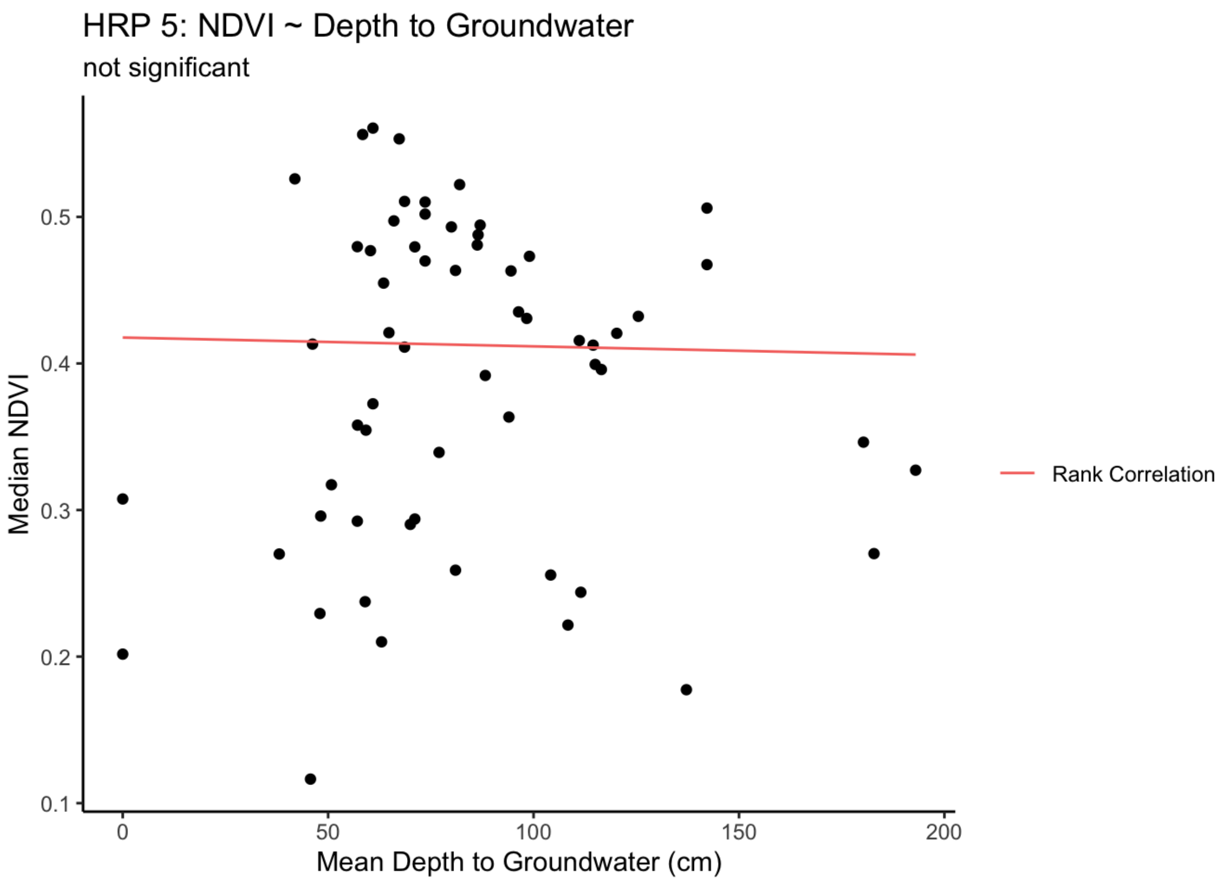
HRP 5 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp4)
##
## Coefficients:
##              Estimate  Std. Error t.value  p.value
## (Intercept)  0.07749858  0.02440929   3.175 0.002456 **
## mean_dtg    -0.00027555  0.00010075  -2.735 0.008379 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.142889
## Reduction in Dispersion Test: 9.16905 p-value: 0.00374
```



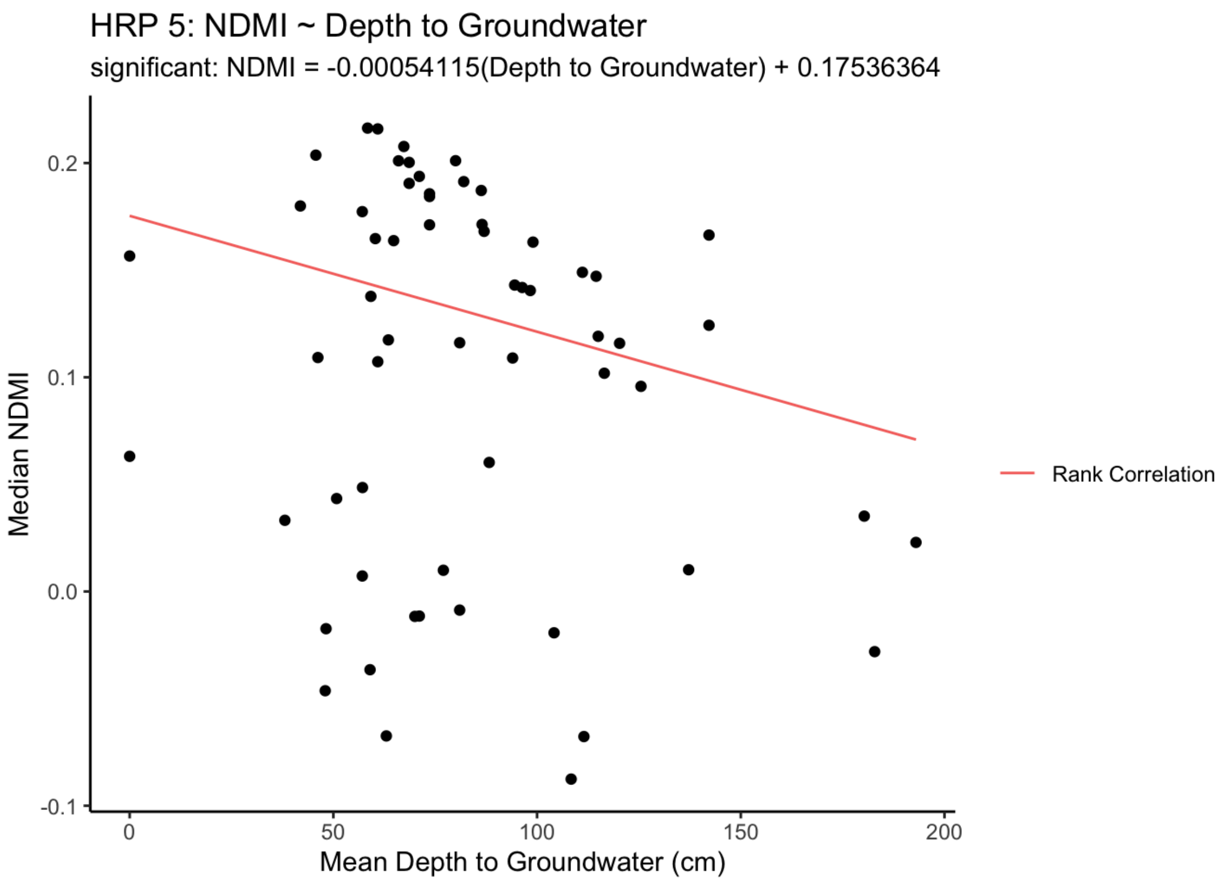
HRP 5 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp5)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  4.1770e-01  4.3759e-02  9.5454 1.691e-13 ***
## mean_dtg    -6.0241e-05  3.9631e-04 -0.1520    0.8797
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0001112422
## Reduction in Dispersion Test: 0.00645 p-value: 0.93625
```



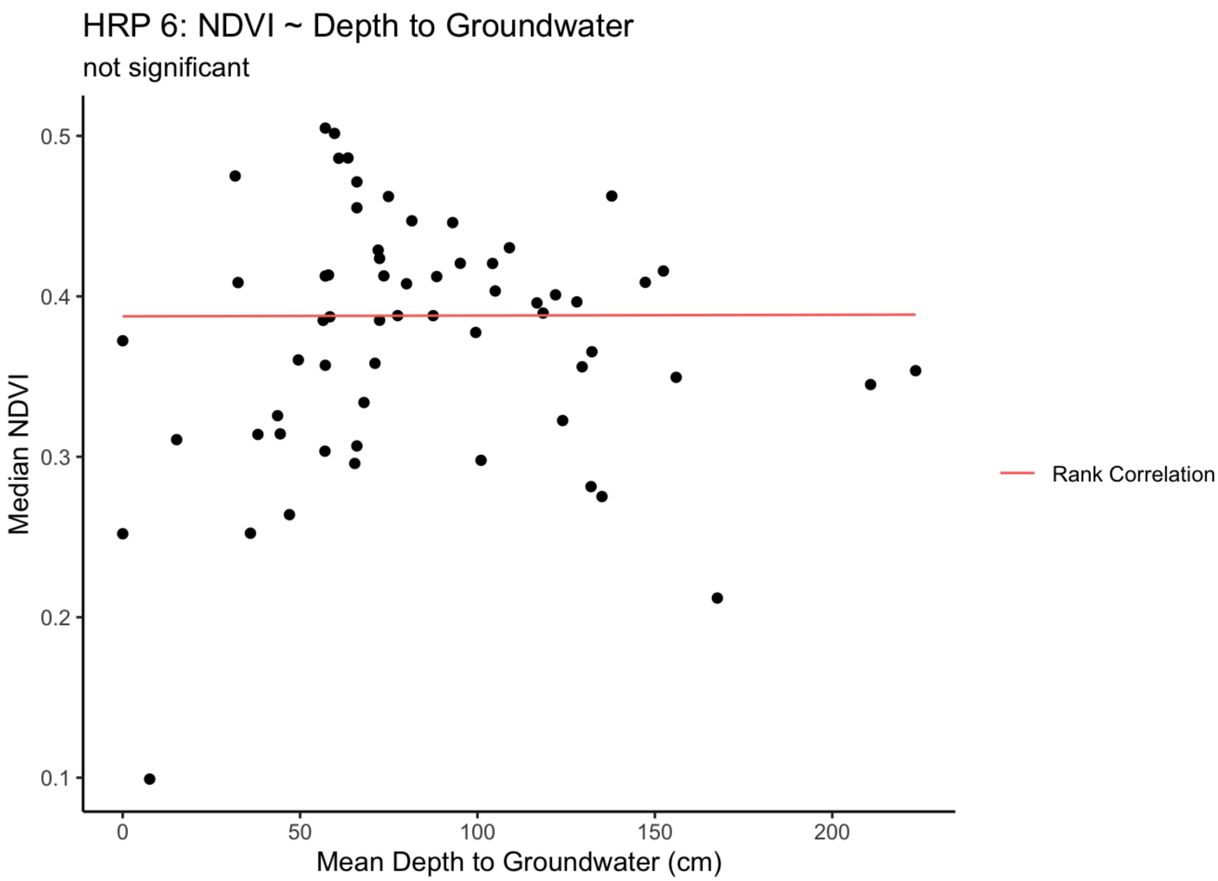
HRP 5 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp5)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.17536364  0.02748472  6.3804 3.191e-08 ***
## mean_dtg    -0.00054115  0.00025121 -2.1542    0.0354 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.05678411
## Reduction in Dispersion Test: 3.49175 p-value: 0.06673
```



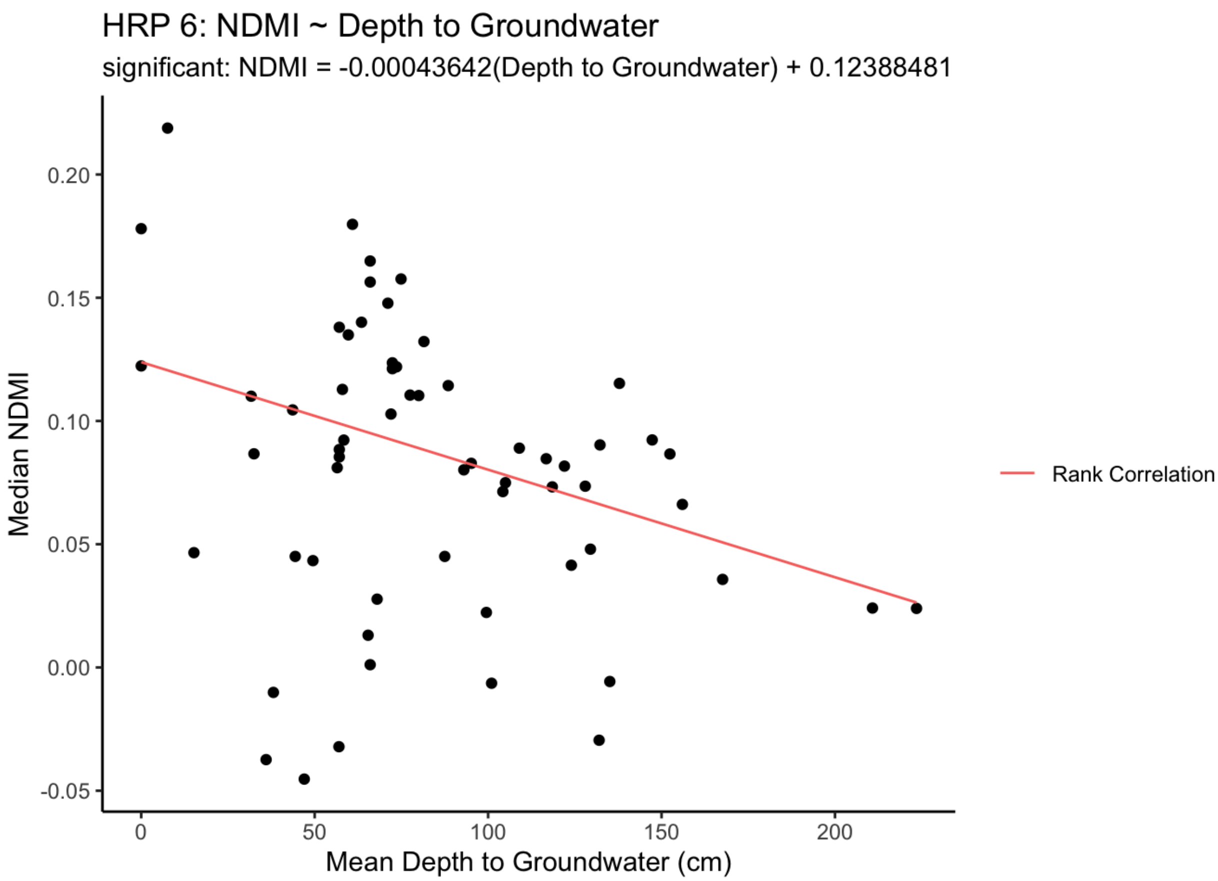
HRP 6 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp6)
##
## Coefficients:
##              Estimate Std. Error t.value p.value
## (Intercept) 3.8756e-01 2.1775e-02 17.7986  <2e-16 ***
## mean_dtg    4.6283e-06 2.0573e-04  0.0225  0.9821
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 1.087886e-05
## Reduction in Dispersion Test: 0.00064 p-value: 0.97987
```



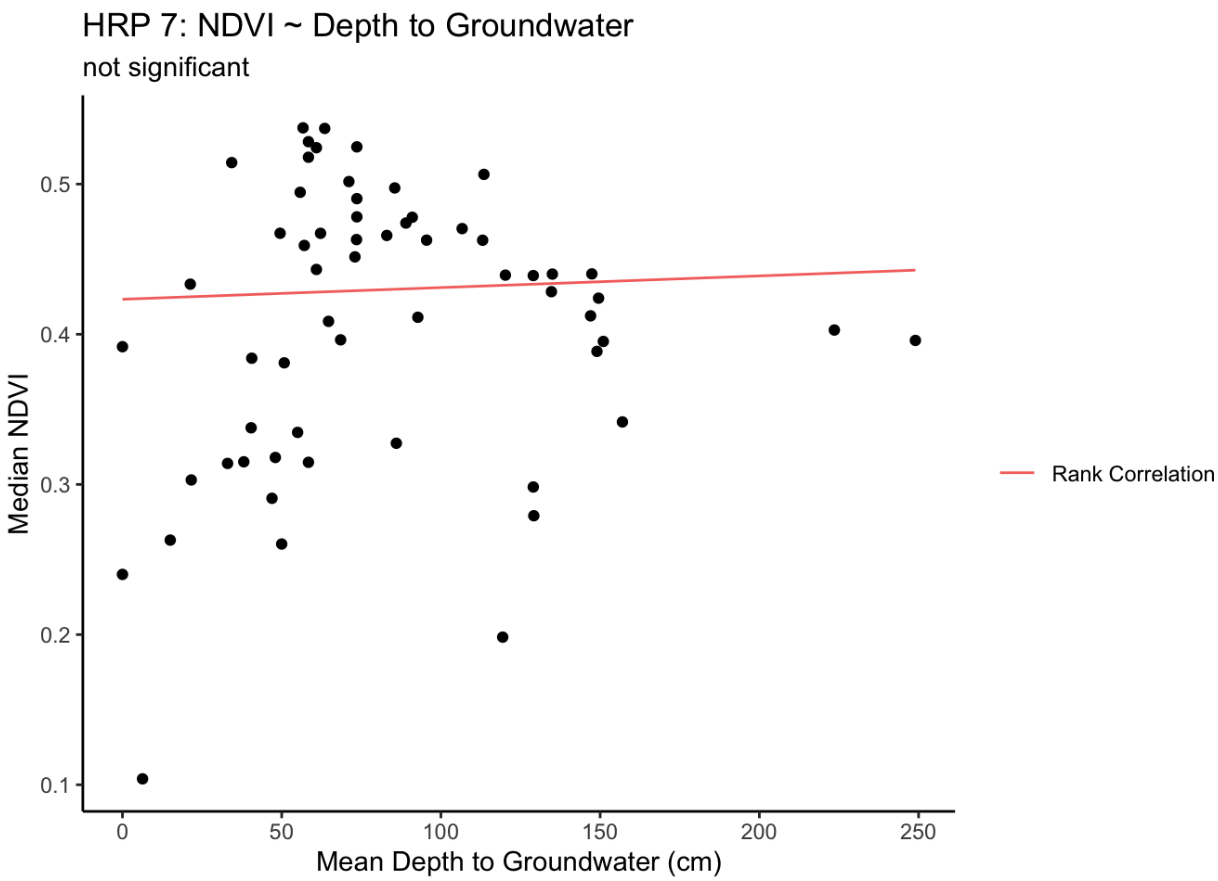
HRP 6 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp6)
##
## Coefficients:
##                Estimate  Std. Error t.value   p.value
## (Intercept)  0.12388481  0.01320493  9.3817 2.656e-13 ***
## mean_dtg    -0.00043642  0.00014289 -3.0543  0.003383 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.1236345
## Reduction in Dispersion Test: 8.32351 p-value: 0.00546
```



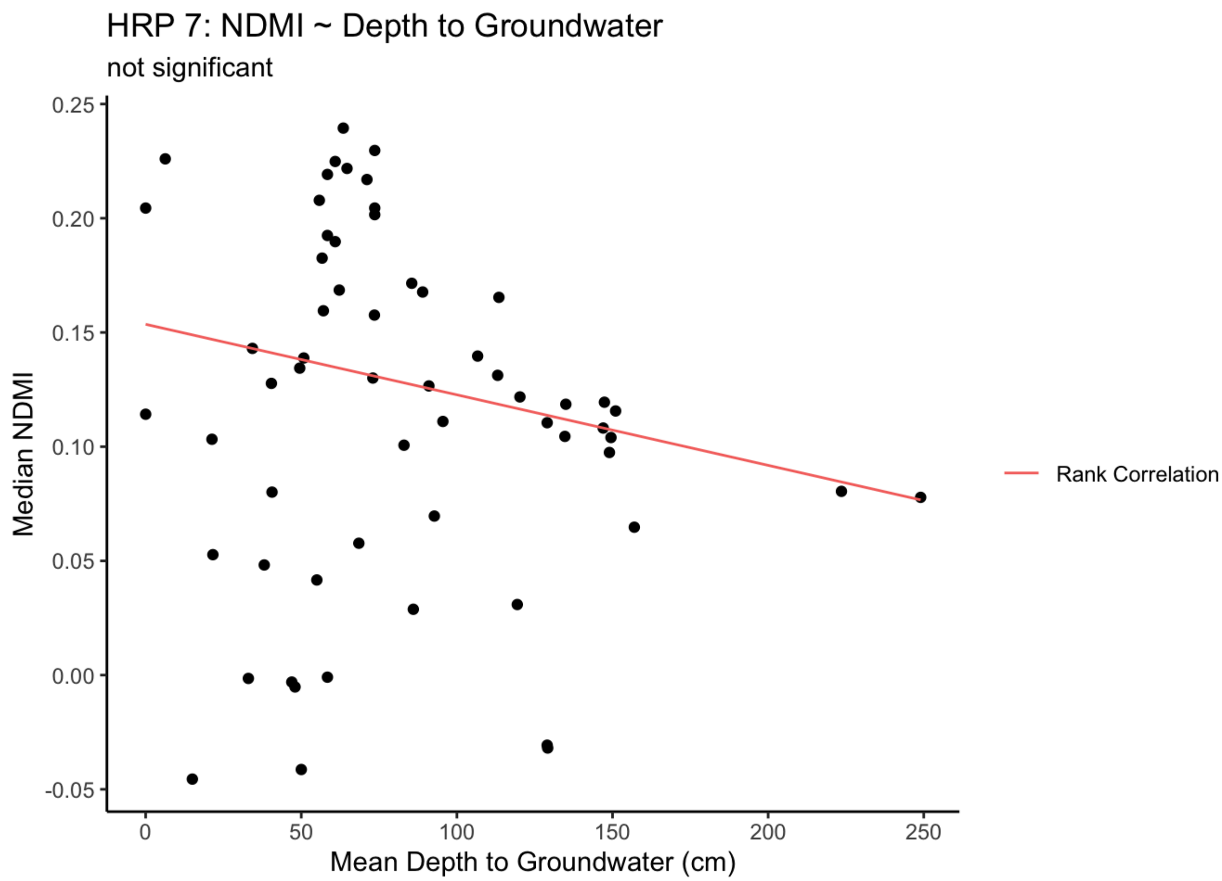
HRP 7 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp7)
##
## Coefficients:
##              Estimate Std. Error t.value p.value
## (Intercept) 4.2331e-01 2.7419e-02 15.4383  <2e-16 ***
## mean_dtg    7.7812e-05 2.4422e-04  0.3186  0.7512
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.002782356
## Reduction in Dispersion Test: 0.16183 p-value: 0.68896
```



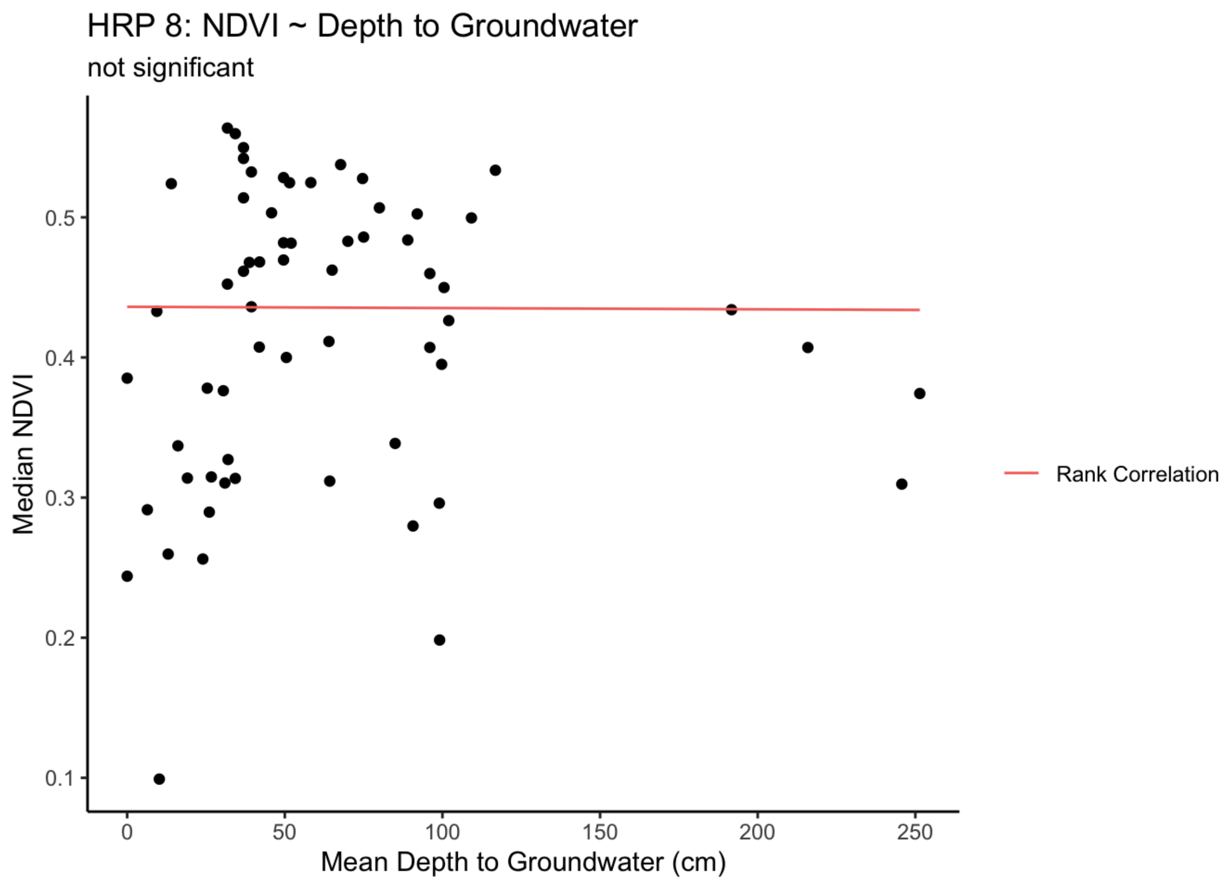
HRP 7 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp7)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.15357120  0.01576094  9.7438 8.049e-14 ***
## mean_dtg    -0.00030873  0.00017321 -1.7824   0.07991 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0513588
## Reduction in Dispersion Test: 3.14008 p-value: 0.08164
```



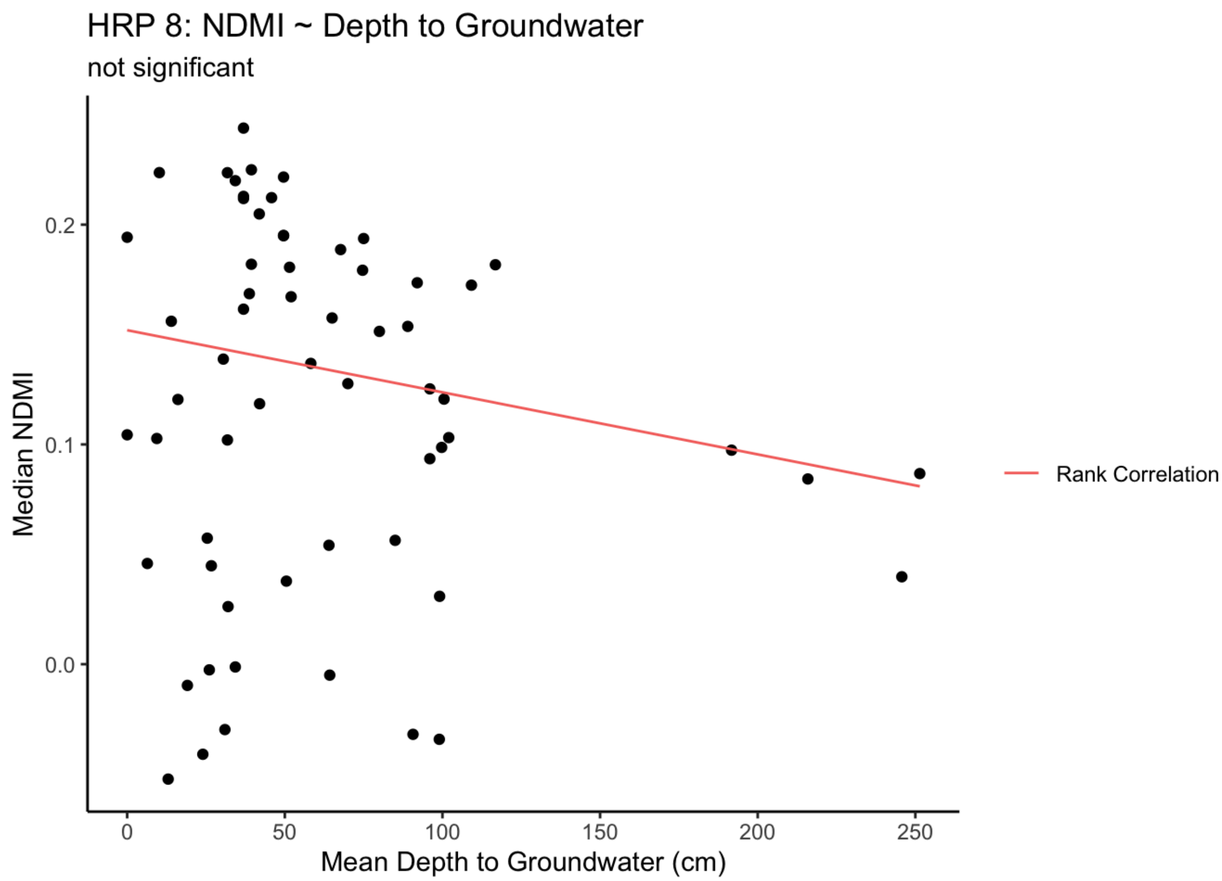
HRP 8 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp8)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  4.3616e-01  2.4674e-02 17.6768  <2e-16 ***
## mean_dtg    -8.9468e-06  2.4236e-04 -0.0369  0.9707
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 3.546449e-05
## Reduction in Dispersion Test: 0.00213 p-value: 0.96336
```



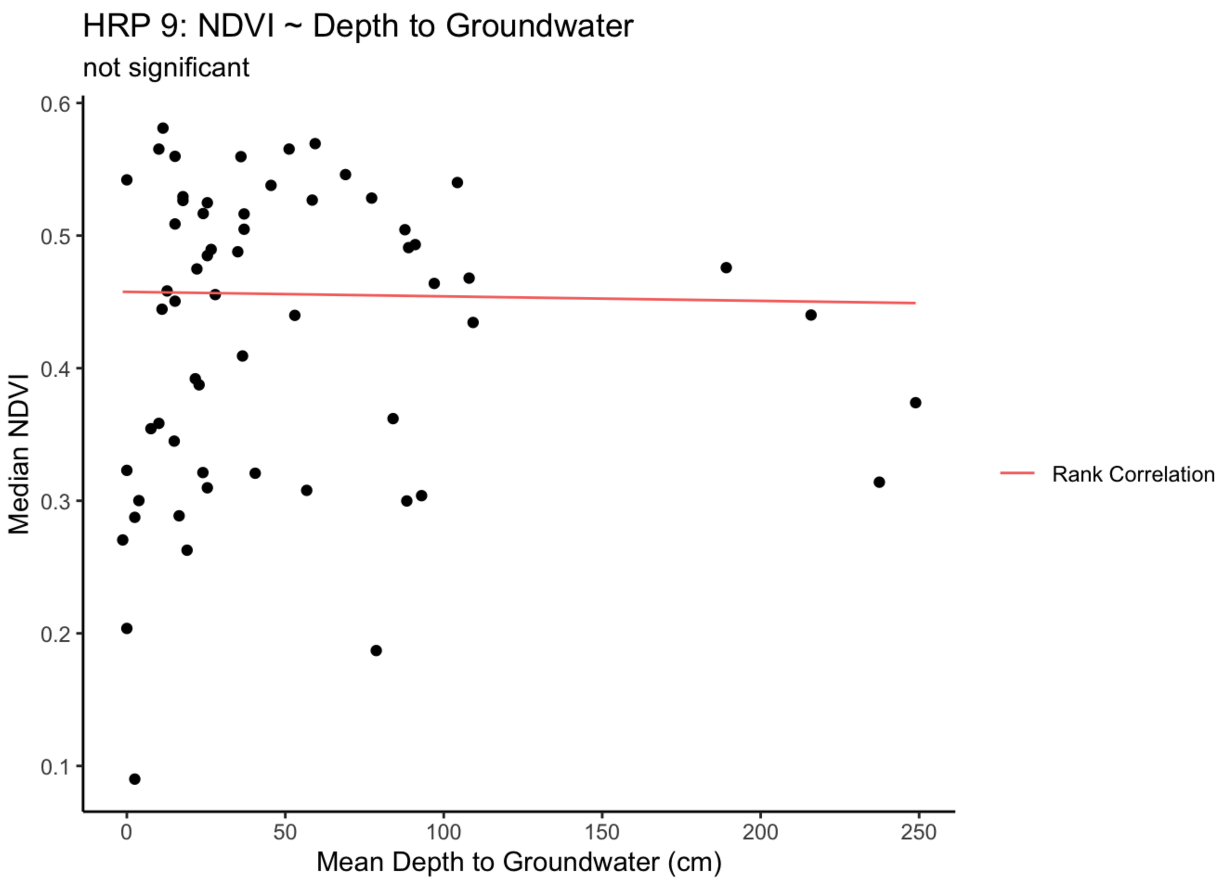
HRP 8 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp8)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.15197661  0.01890756  8.0379 4.223e-11 ***
## mean_dtg    -0.00028253  0.00019677 -1.4358    0.1562
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.02967777
## Reduction in Dispersion Test: 1.83513 p-value: 0.1806
```



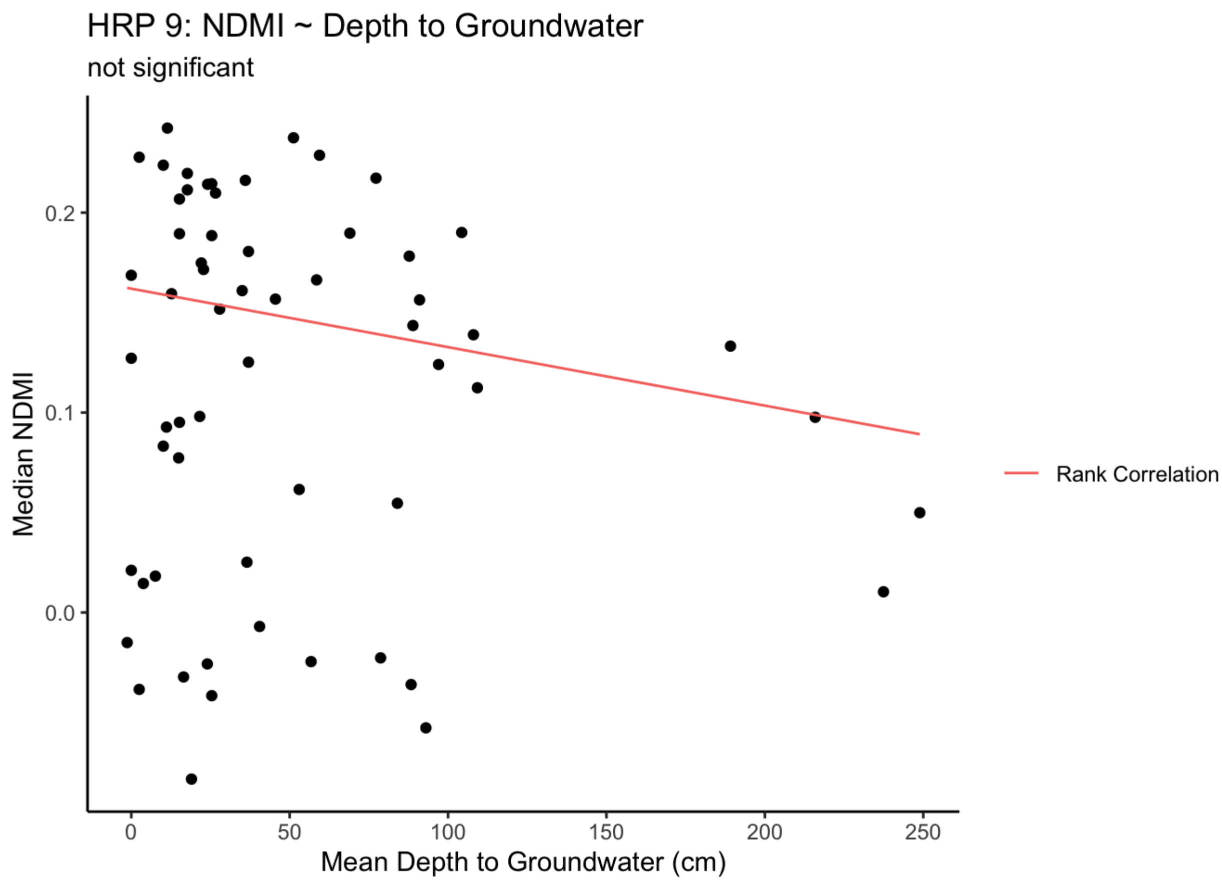
HRP 9 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp9)
##
## Coefficients:
##               Estimate  Std. Error t.value p.value
## (Intercept)  4.5757e-01  3.0225e-02 15.1384  <2e-16 ***
## mean_dtg    -3.3947e-05  2.3819e-04 -0.1425  0.8872
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0002859514
## Reduction in Dispersion Test: 0.01659 p-value: 0.89796
```



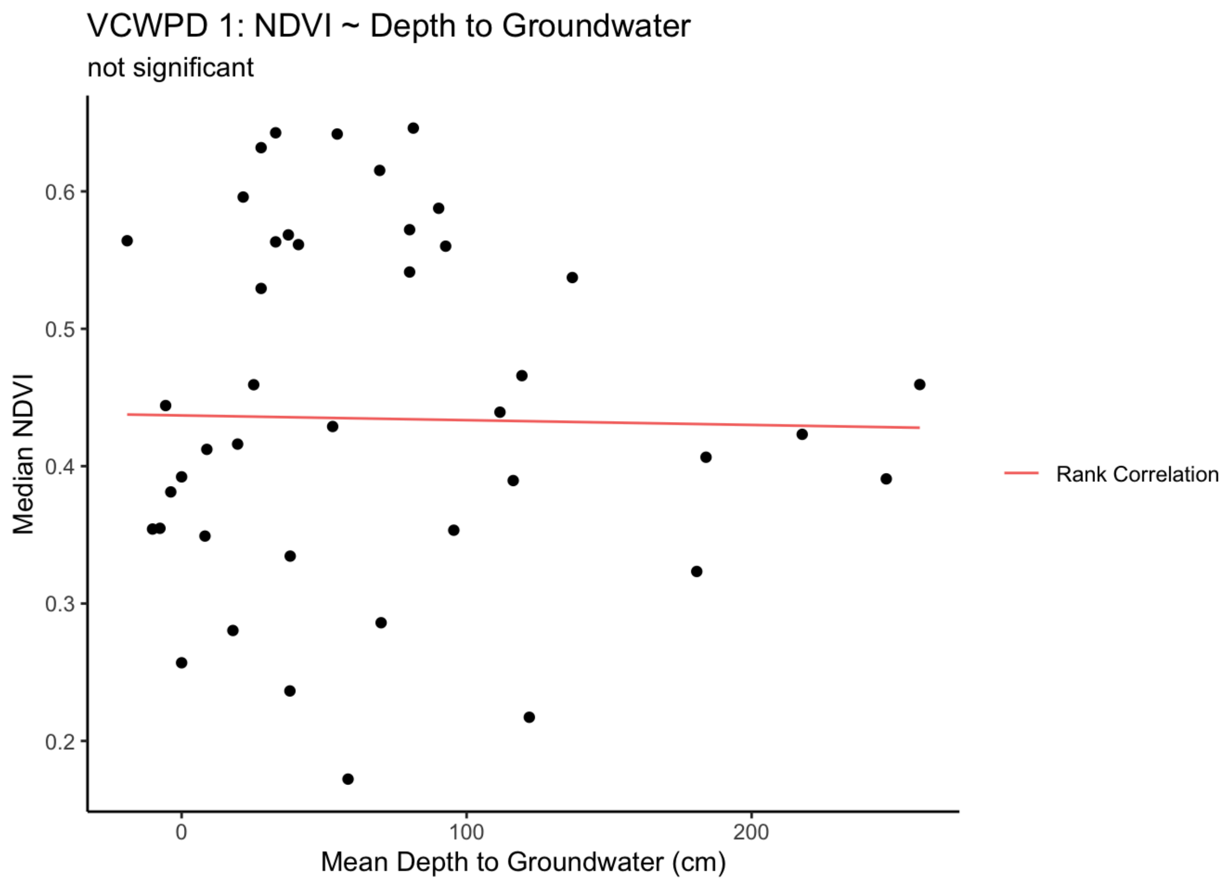
HRP 9 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp9)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.16197876  0.02390543  6.7758 6.969e-09 ***
## mean_dtg    -0.00029248  0.00019089 -1.5322    0.1309
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.02994057
## Reduction in Dispersion Test: 1.79015 p-value: 0.18613
```



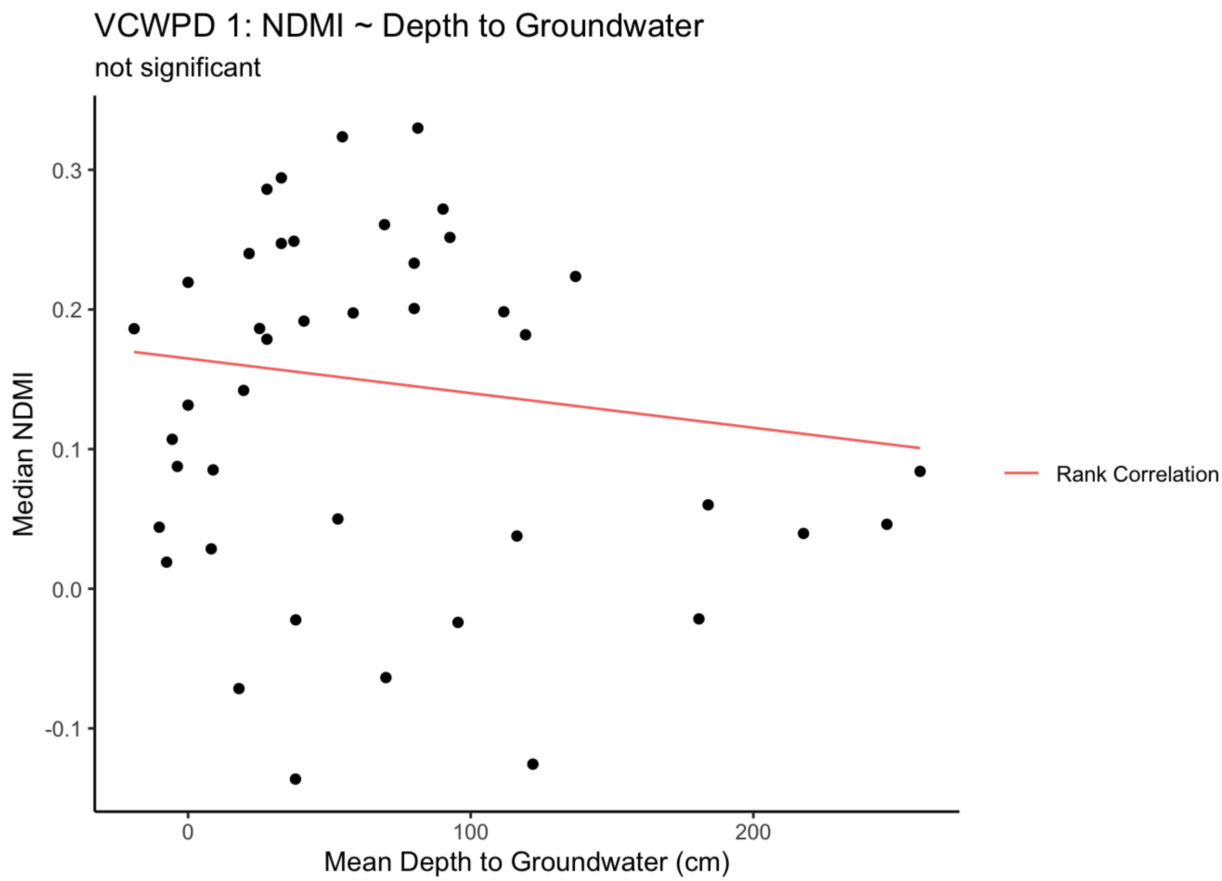
VCWPD 1 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc1)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  4.3693e-01  4.4311e-02  9.8605 2.892e-12 ***
## mean_dtg    -3.4559e-05  3.0113e-04 -0.1148    0.9092
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0004662098
## Reduction in Dispersion Test: 0.01866 p-value: 0.89204
```



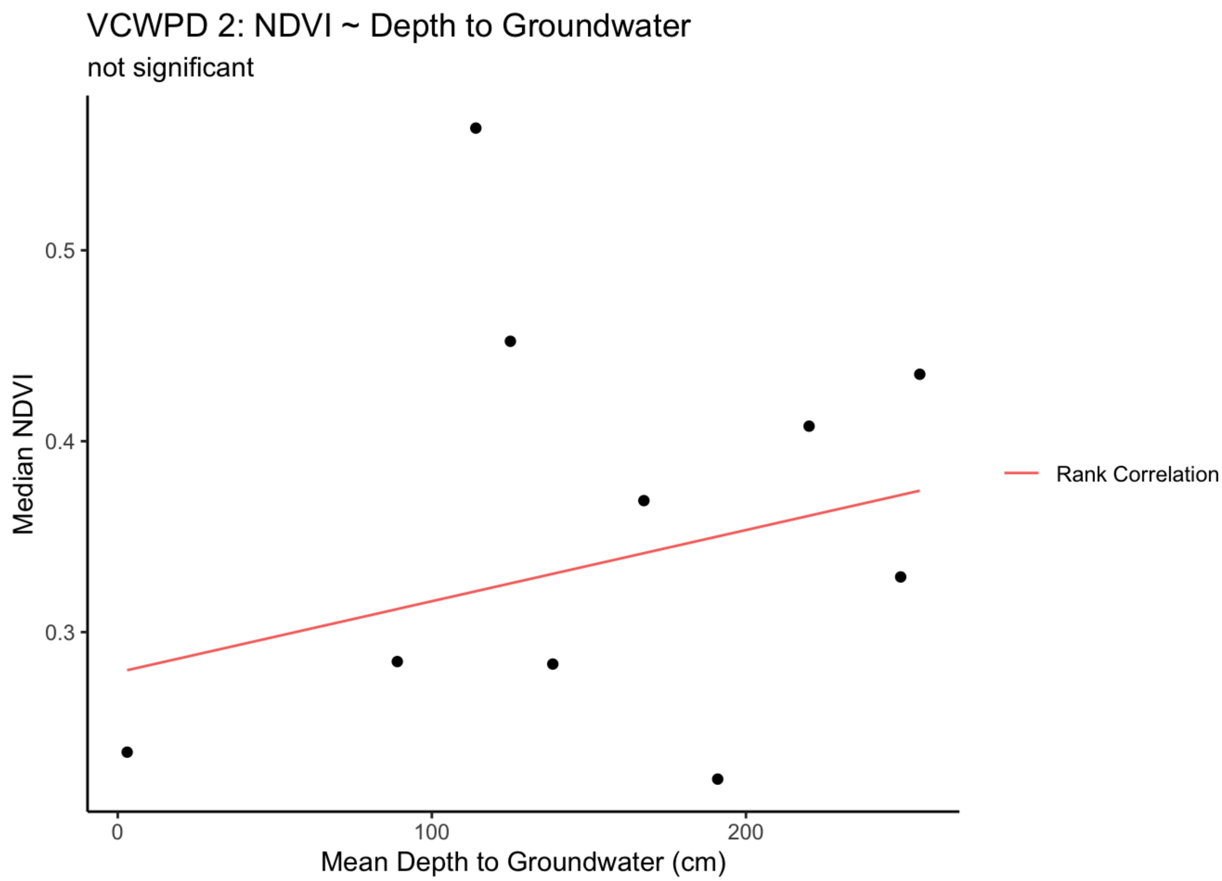
VCWPD 1 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc1)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.16486501  0.03984526  4.1376 0.0001753 ***
## mean_dtg    -0.00024763  0.00032149 -0.7703 0.4456739
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0199036
## Reduction in Dispersion Test: 0.81231 p-value: 0.37283
```



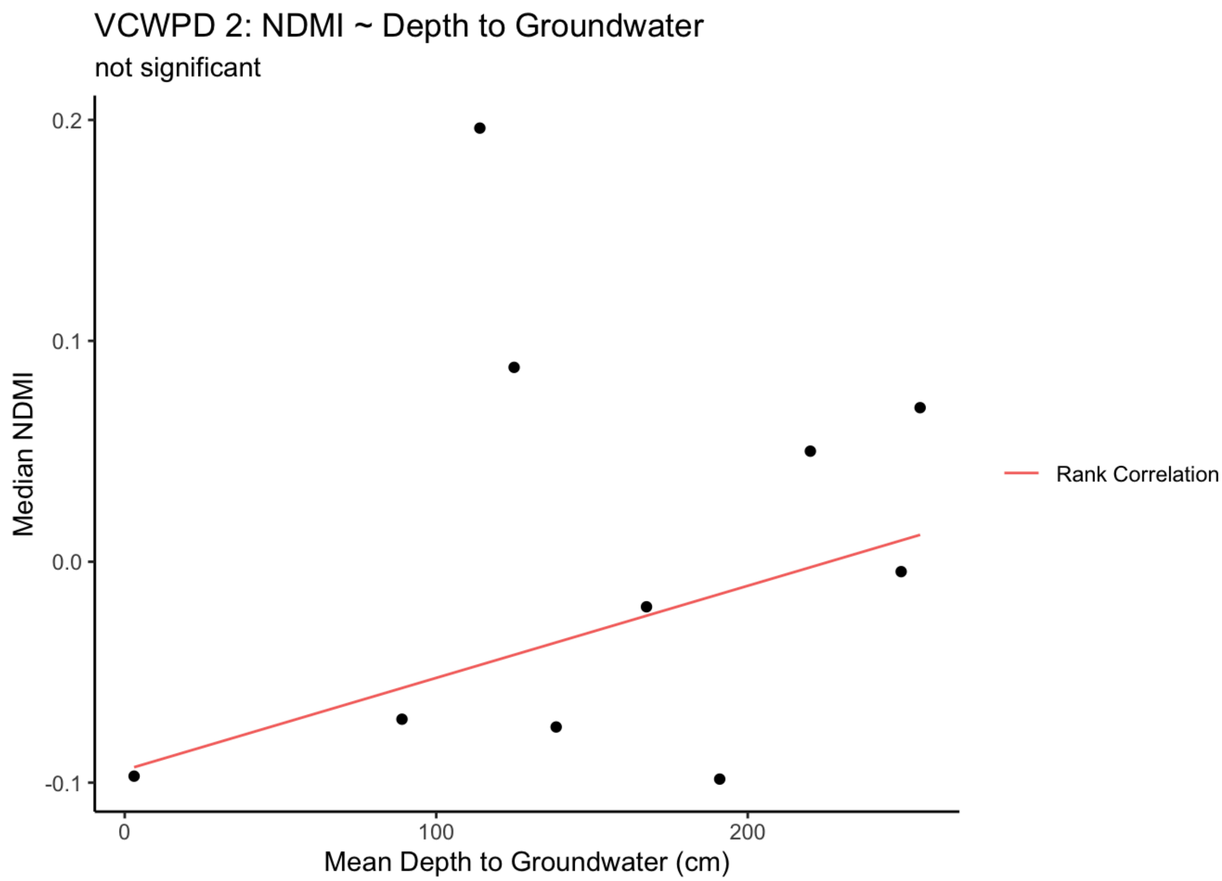
VCWPD 2 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc2)
##
## Coefficients:
##             Estimate Std. Error t.value p.value
## (Intercept) 0.27893197 0.12450058  2.2404 0.05539 .
## mean_dtg    0.00037266 0.00072530  0.5138 0.62128
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.08685165
## Reduction in Dispersion Test: 0.7609 p-value: 0.40846
```



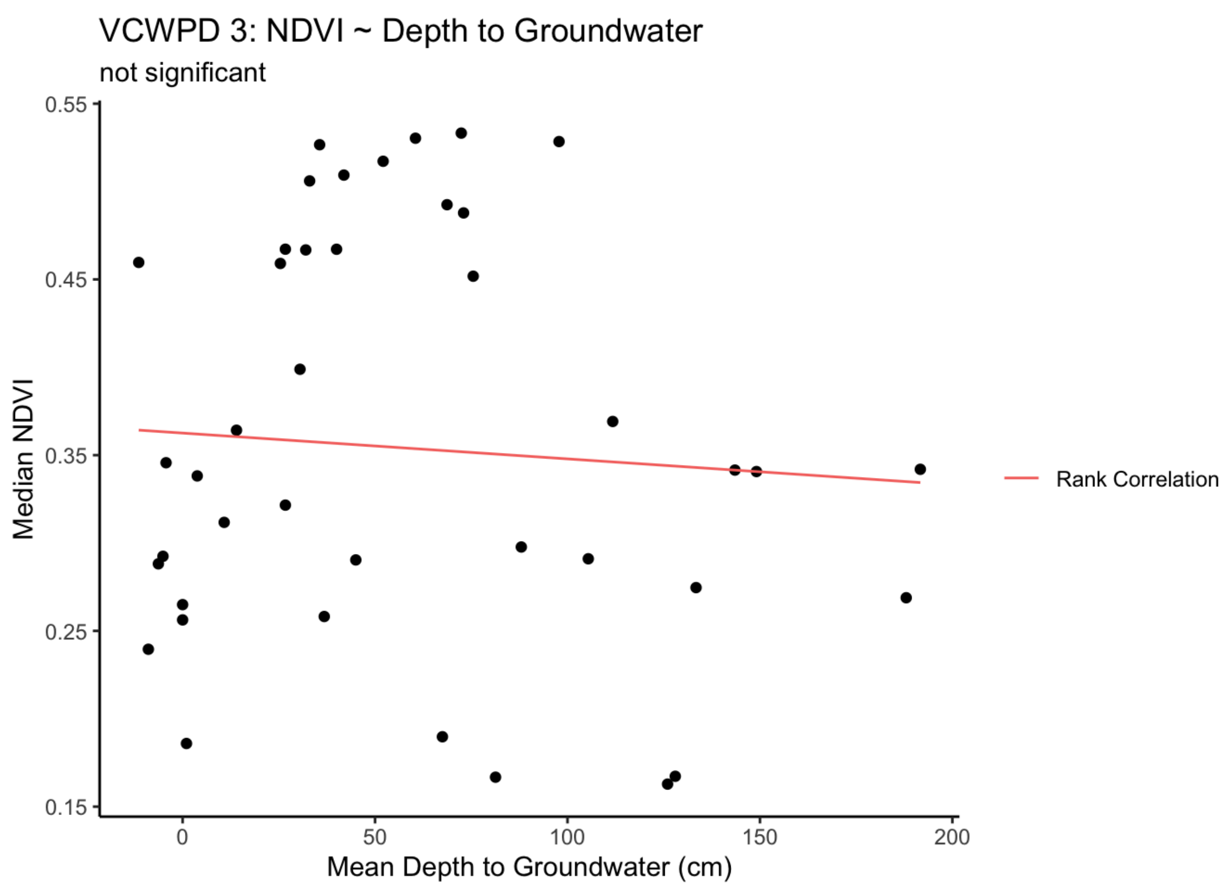
VCWPD 2 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc2)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept) -0.09426662  0.09035212 -1.0433  0.3273
## mean_dtg     0.00041689  0.00047877  0.8707  0.4093
##
## Multiple R-squared (Robust): 0.1288386
## Reduction in Dispersion Test: 1.18314 p-value: 0.3084
```



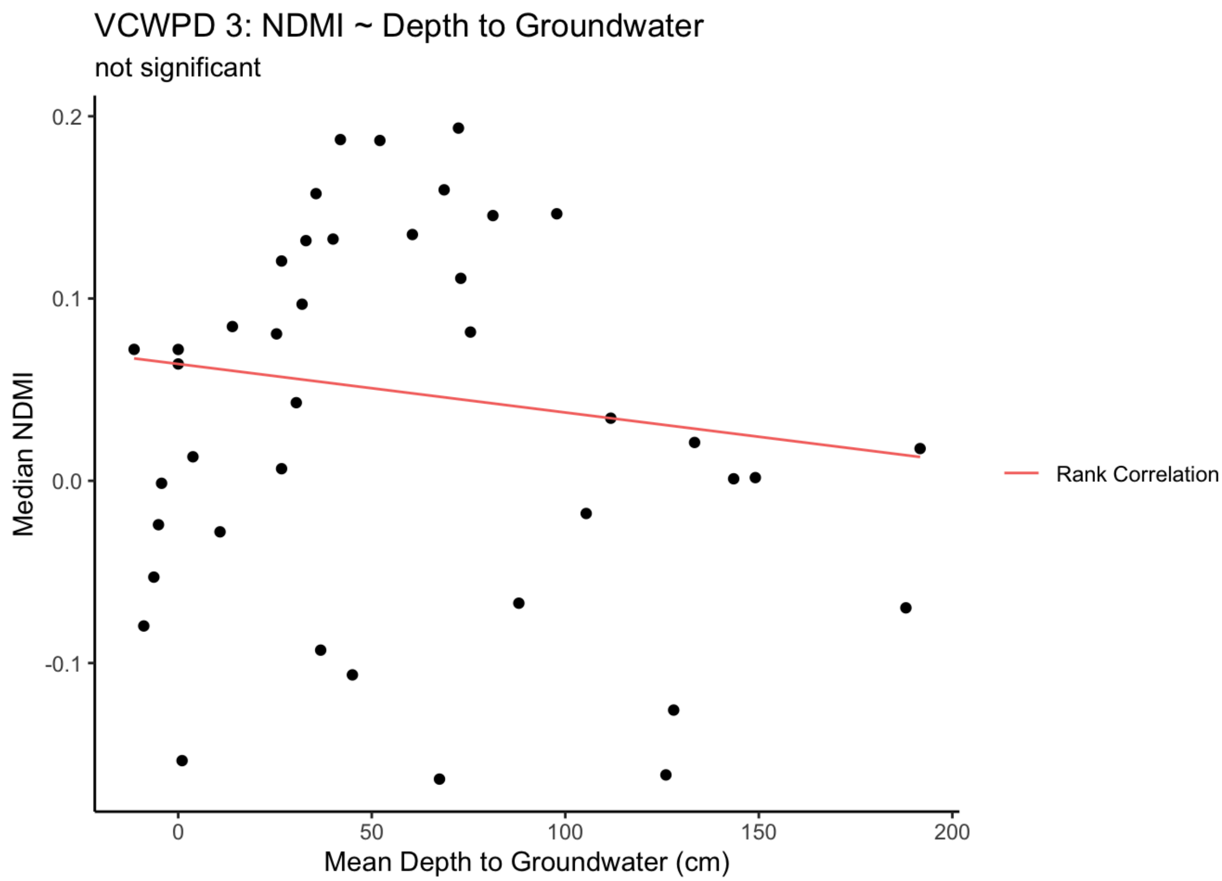
VCWPD 3 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc3)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.36256903  0.04820857  7.5208 4.174e-09 ***
## mean_dtg    -0.00014689  0.00034144 -0.4302    0.6694
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.005792228
## Reduction in Dispersion Test: 0.22721 p-value: 0.63626
```



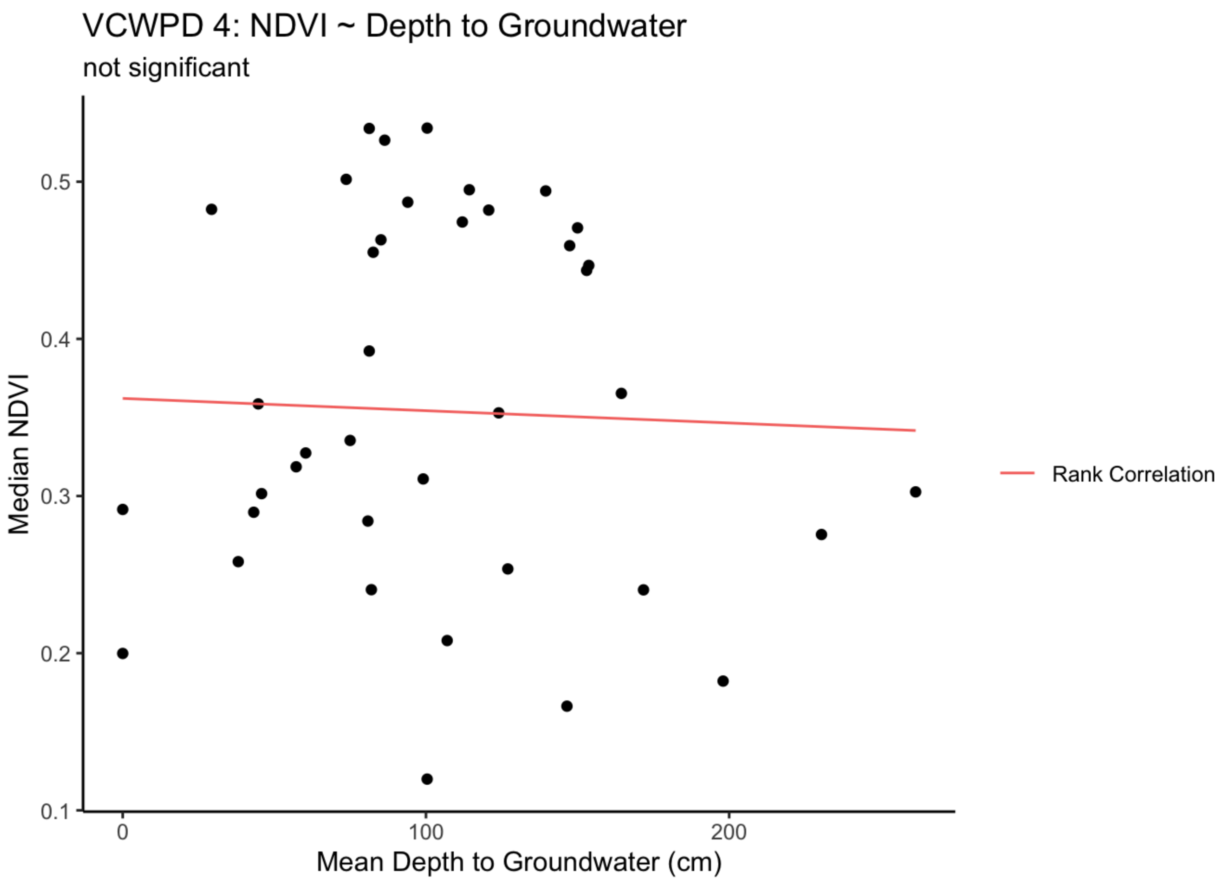
VCWPD 3 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc3)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  0.06409781  0.03135847  2.0440 0.04774 *
## mean_dtg    -0.00026629  0.00034205 -0.7785 0.44097
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.01393095
## Reduction in Dispersion Test: 0.55098 p-value: 0.46236
```



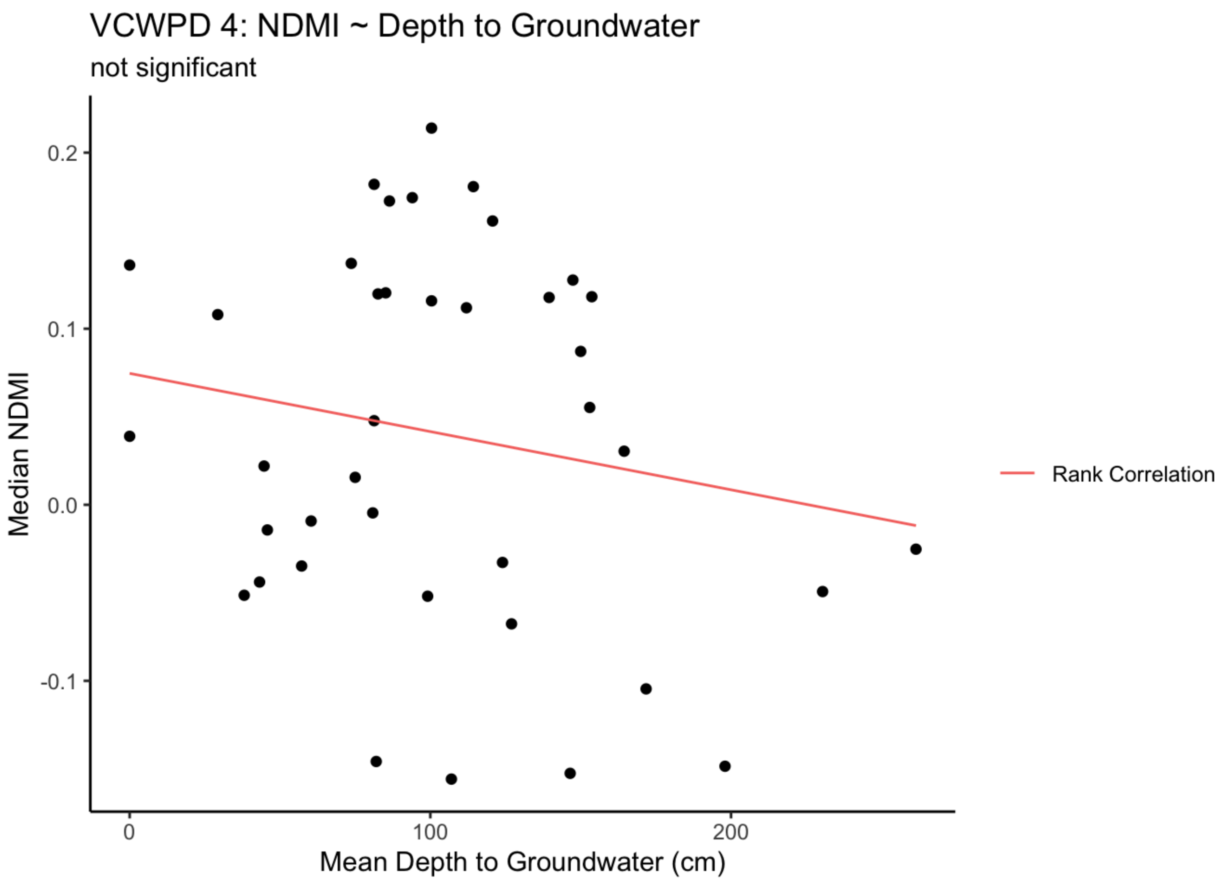
VCWPD 4 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc4)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  3.6211e-01  5.7785e-02  6.2664 2.738e-07 ***
## mean_dtg    -7.8113e-05  3.2574e-04 -0.2398    0.8118
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.003318981
## Reduction in Dispersion Test: 0.12321 p-value: 0.72757
```



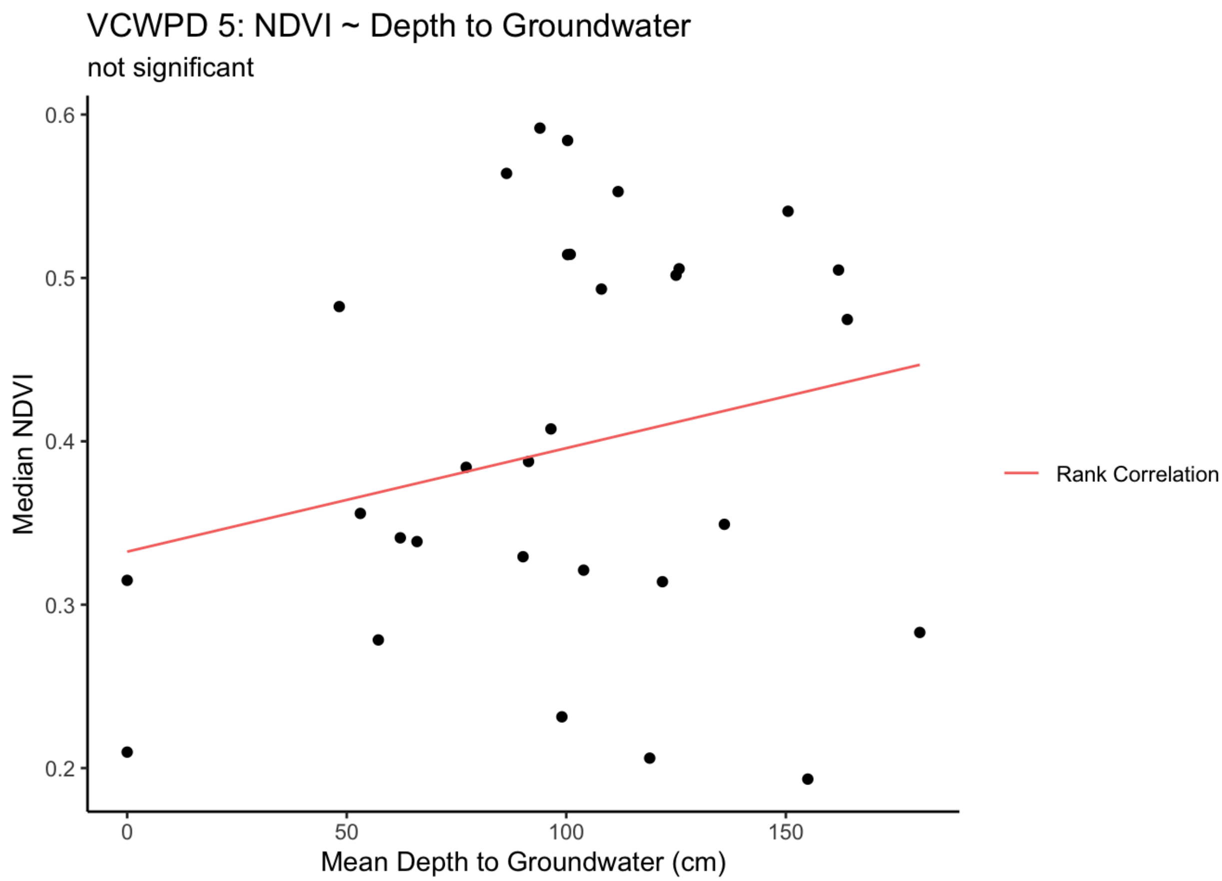
VCWPD 4 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc4)
##
## Coefficients:
##               Estimate  Std. Error t.value p.value
## (Intercept)  0.07463118  0.04993706  1.4945  0.1435
## mean_dtg    -0.00033060  0.00032631 -1.0131  0.3176
##
## Multiple R-squared (Robust): 0.03155565
## Reduction in Dispersion Test: 1.2056 p-value: 0.2793
```



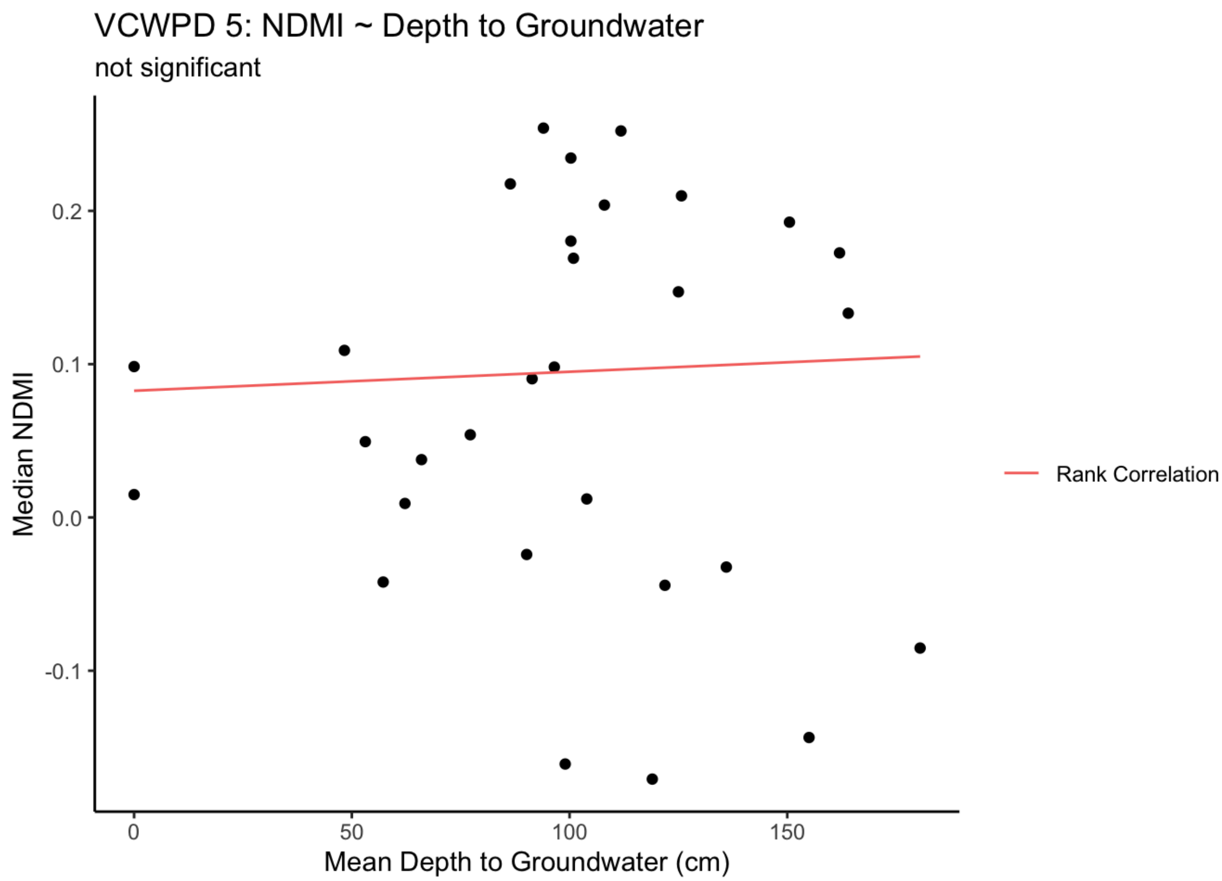
VCWPD 5 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc5)
##
## Coefficients:
##              Estimate Std. Error t.value   p.value
## (Intercept) 0.33244587 0.07179400  4.6306 7.612e-05 ***
## mean_dtg    0.00063378 0.00059199  1.0706    0.2935
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.03471725
## Reduction in Dispersion Test: 1.00704 p-value: 0.32421
```



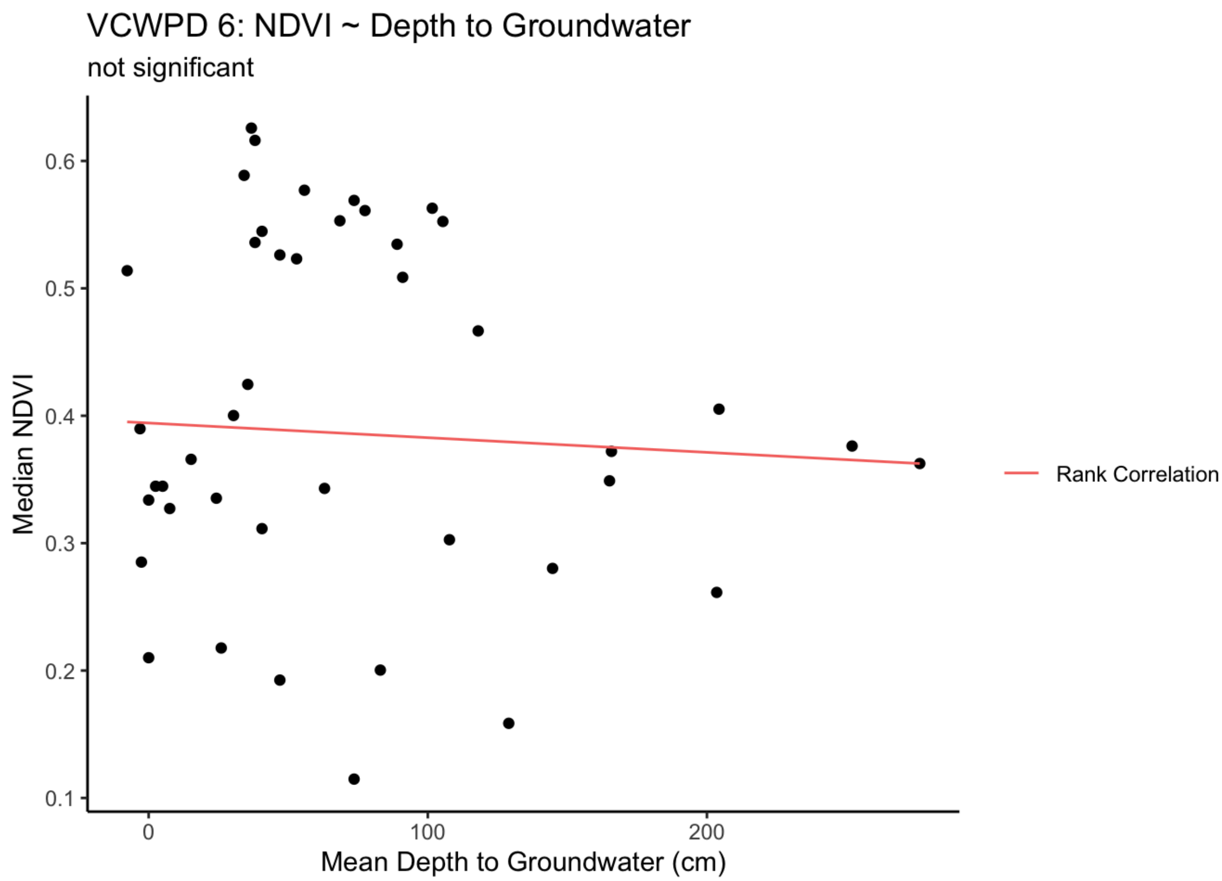
VCWPD 5 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc5)
##
## Coefficients:
##             Estimate Std. Error t.value p.value
## (Intercept) 0.08264372 0.07825158  1.0561  0.2999
## mean_dtg    0.00012388 0.00067183  0.1844  0.8550
##
## Multiple R-squared (Robust): 0.000849614
## Reduction in Dispersion Test: 0.02381 p-value: 0.87848
```



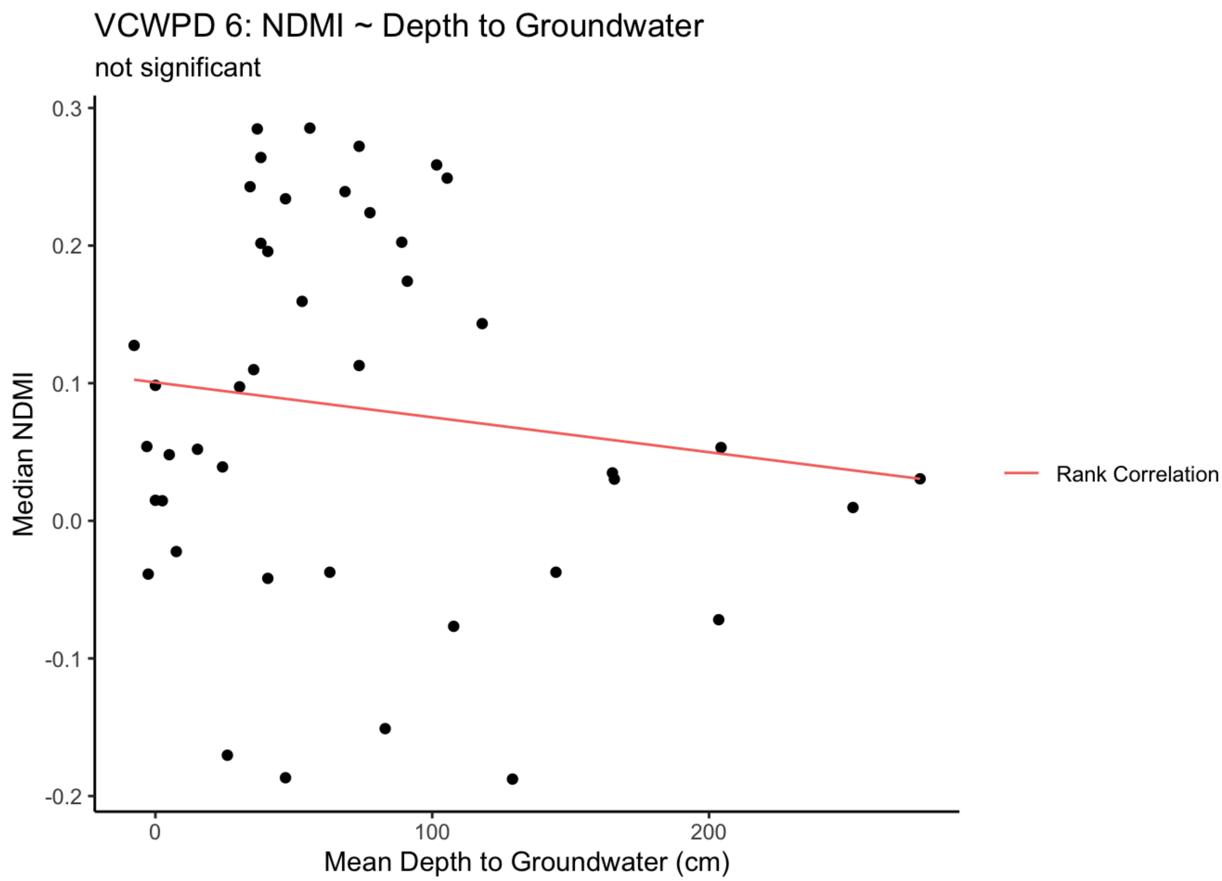
VCWPD 6 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc6)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.39429654  0.05079457  7.7626 1.412e-09 ***
## mean_dtg    -0.00011511  0.00029148 -0.3949     0.695
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.004399026
## Reduction in Dispersion Test: 0.18116 p-value: 0.67261
```



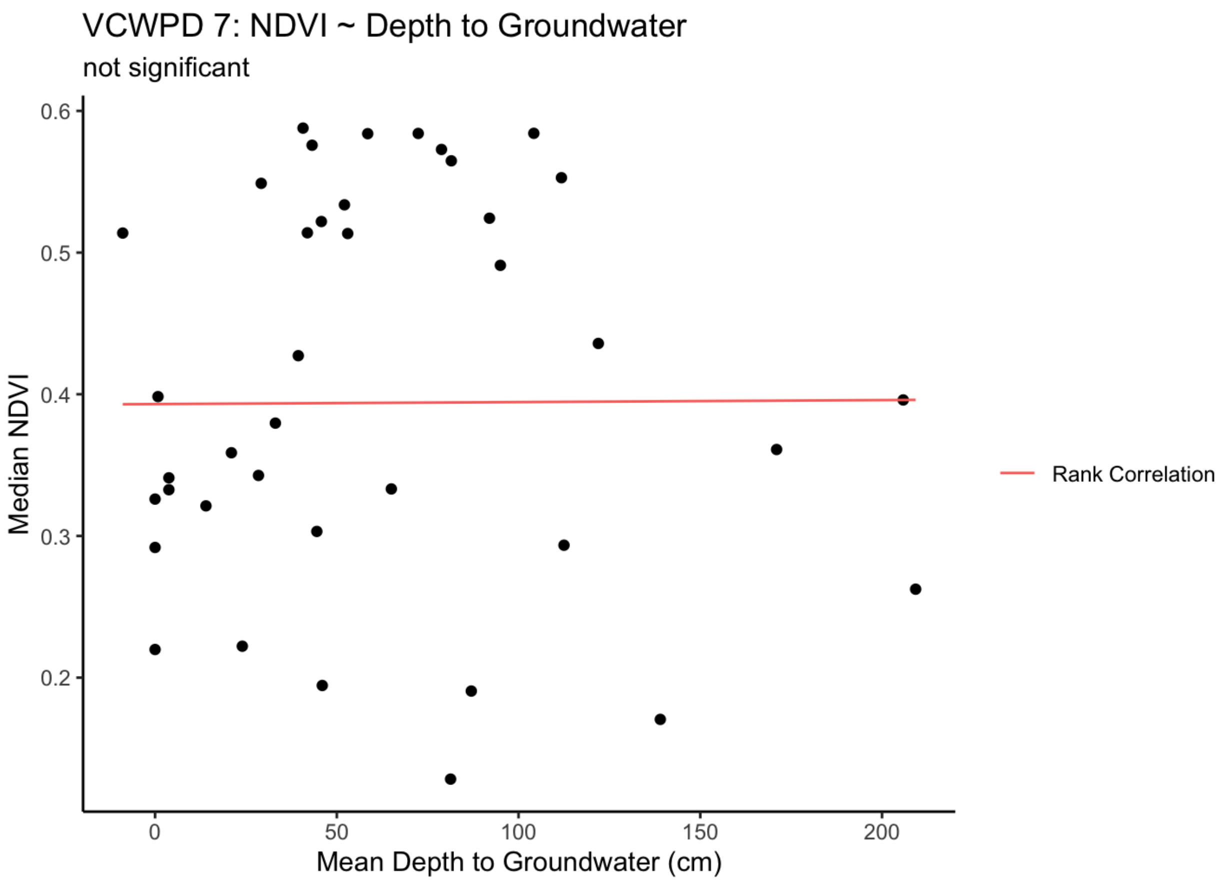
VCWPD 6 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc6)
##
## Coefficients:
##                Estimate  Std. Error t.value p.value
## (Intercept)  0.10057779  0.04009567  2.5084 0.01618 *
## mean_dtg    -0.00025363  0.00031451 -0.8064 0.42466
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.02066794
## Reduction in Dispersion Test: 0.86527 p-value: 0.35771
```



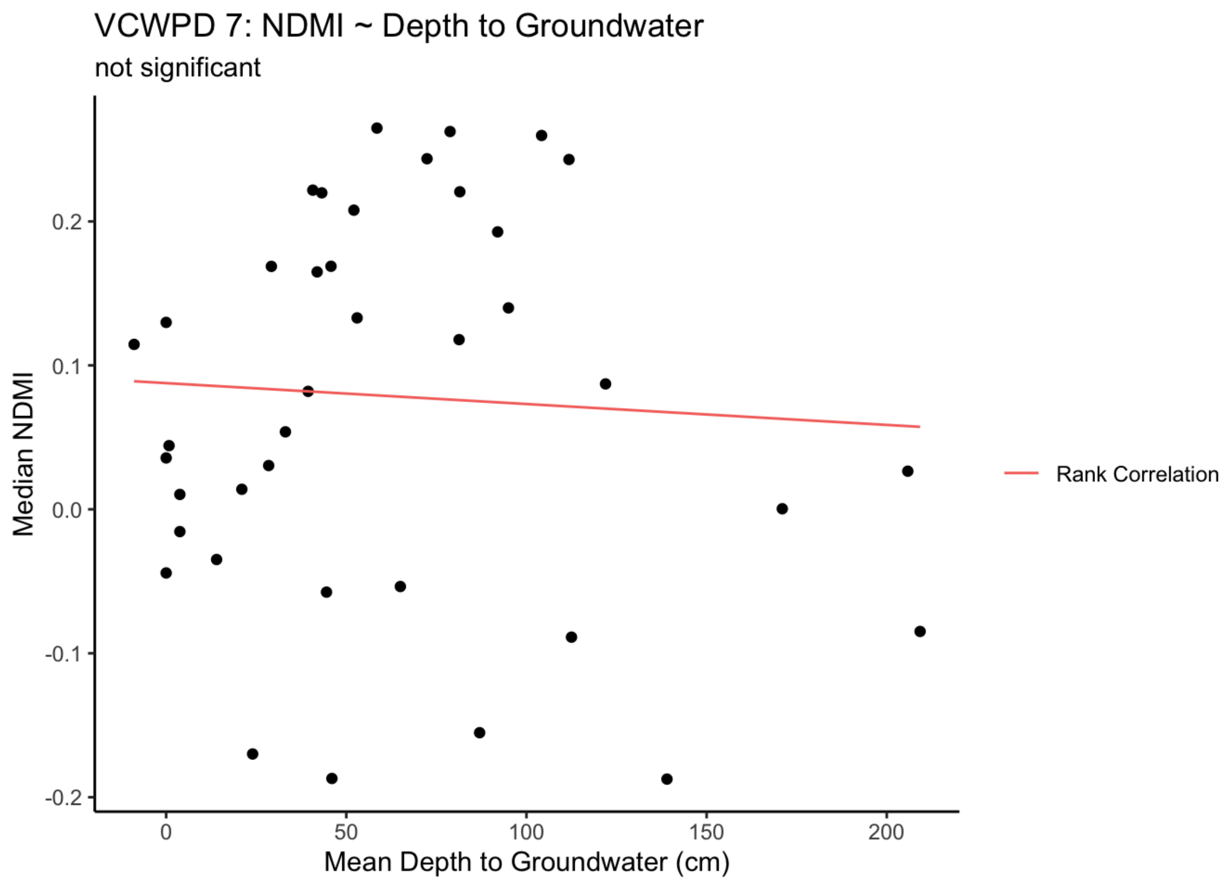
VCWPD 7 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc7)
##
## Coefficients:
##               Estimate Std. Error t.value   p.value
## (Intercept) 0.39307417 0.05359773  7.3338 1.023e-08 ***
## mean_dtg    0.00001413 0.00037318  0.0379      0.97
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 5.734796e-05
## Reduction in Dispersion Test: 0.00212 p-value: 0.96351
```



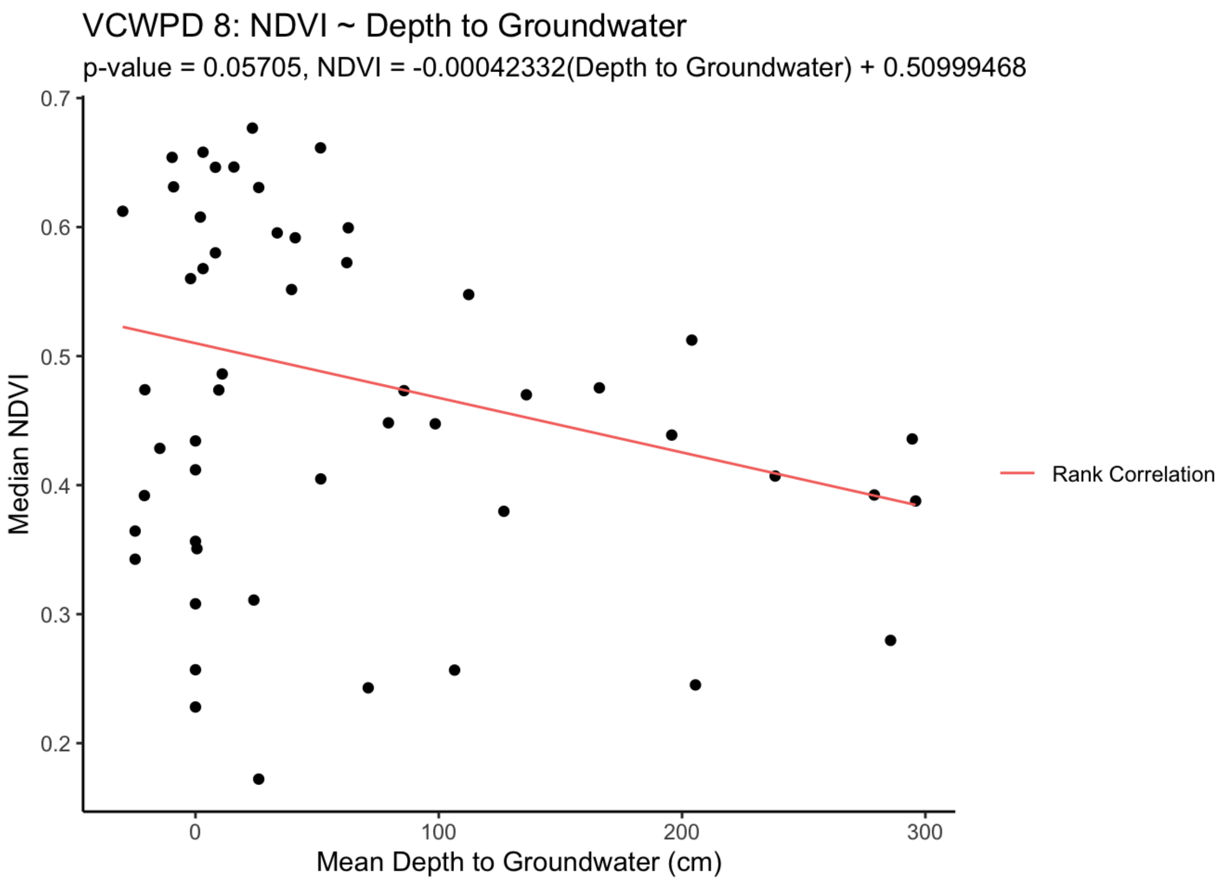
VCWPD 7 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc7)
##
## Coefficients:
##                Estimate  Std. Error t.value p.value
## (Intercept)  0.08767207  0.05068526  1.7297 0.09201 .
## mean_dtg    -0.00014511  0.00047789 -0.3037 0.76309
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.002228692
## Reduction in Dispersion Test: 0.08265 p-value: 0.77535
```



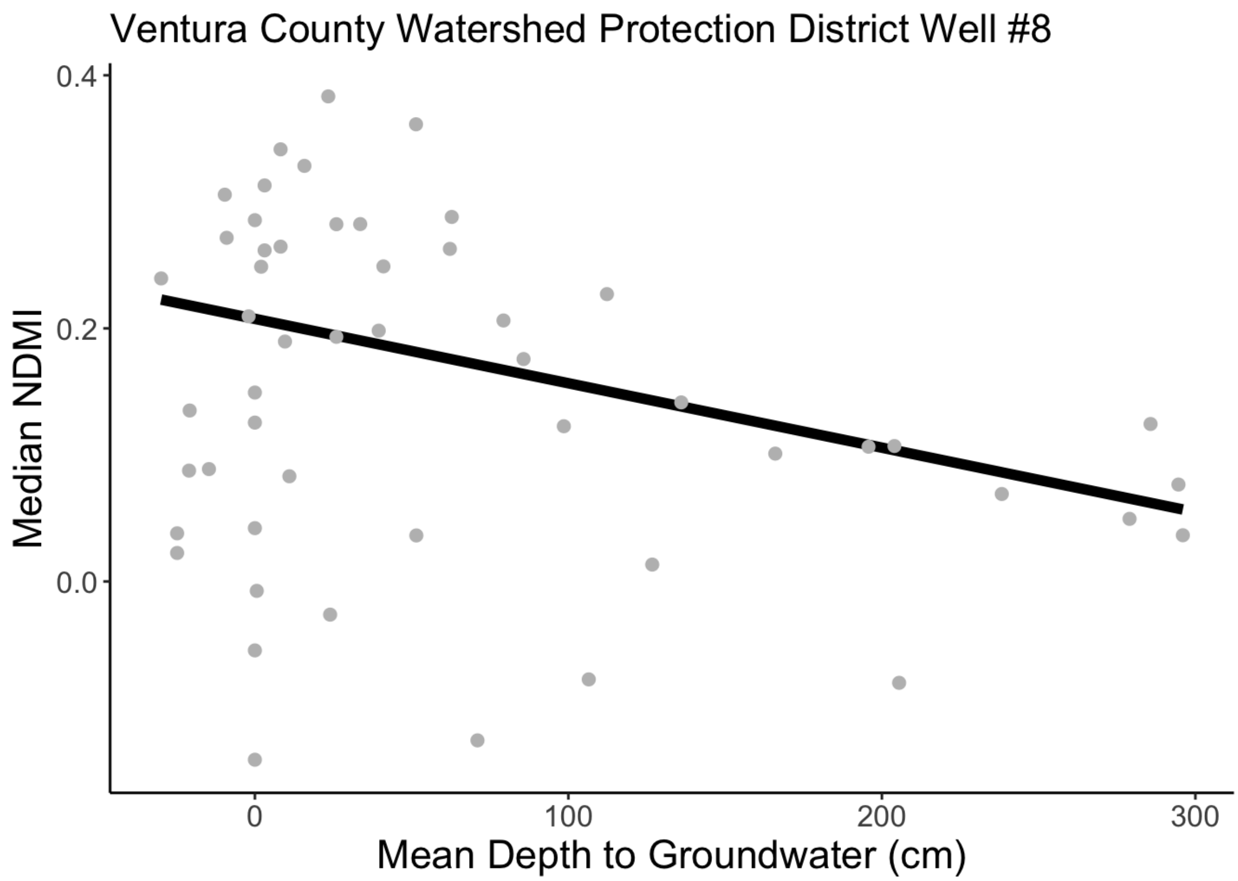
VCWPD 8 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc8)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  0.50999468  0.03787728 13.4644 < 2e-16 ***
## mean_dtg    -0.00042332  0.00021732 -1.9479 0.05705 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.0637347
## Reduction in Dispersion Test: 3.40367 p-value: 0.07098
```



VCWPD 8 NDMI

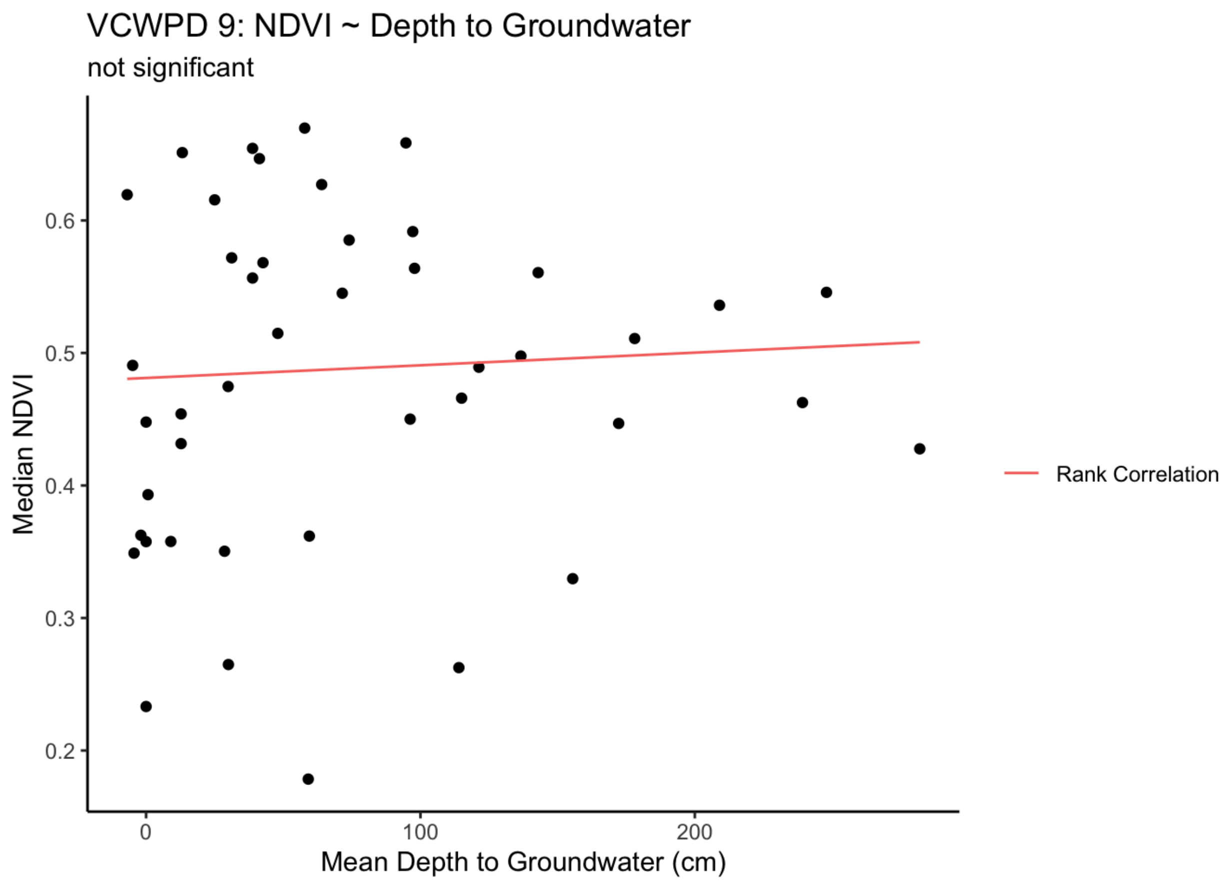
```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc8)
##
## Coefficients:
##               Estimate  Std. Error t.value  p.value
## (Intercept)  0.20753733  0.02285689  9.0799 3.73e-12 ***
## mean_dtg    -0.00050893  0.00018920 -2.6899 0.009689 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.1094074
## Reduction in Dispersion Test: 6.1424 p-value: 0.01662
```




```
Unset
## [1] -0.1408458
```

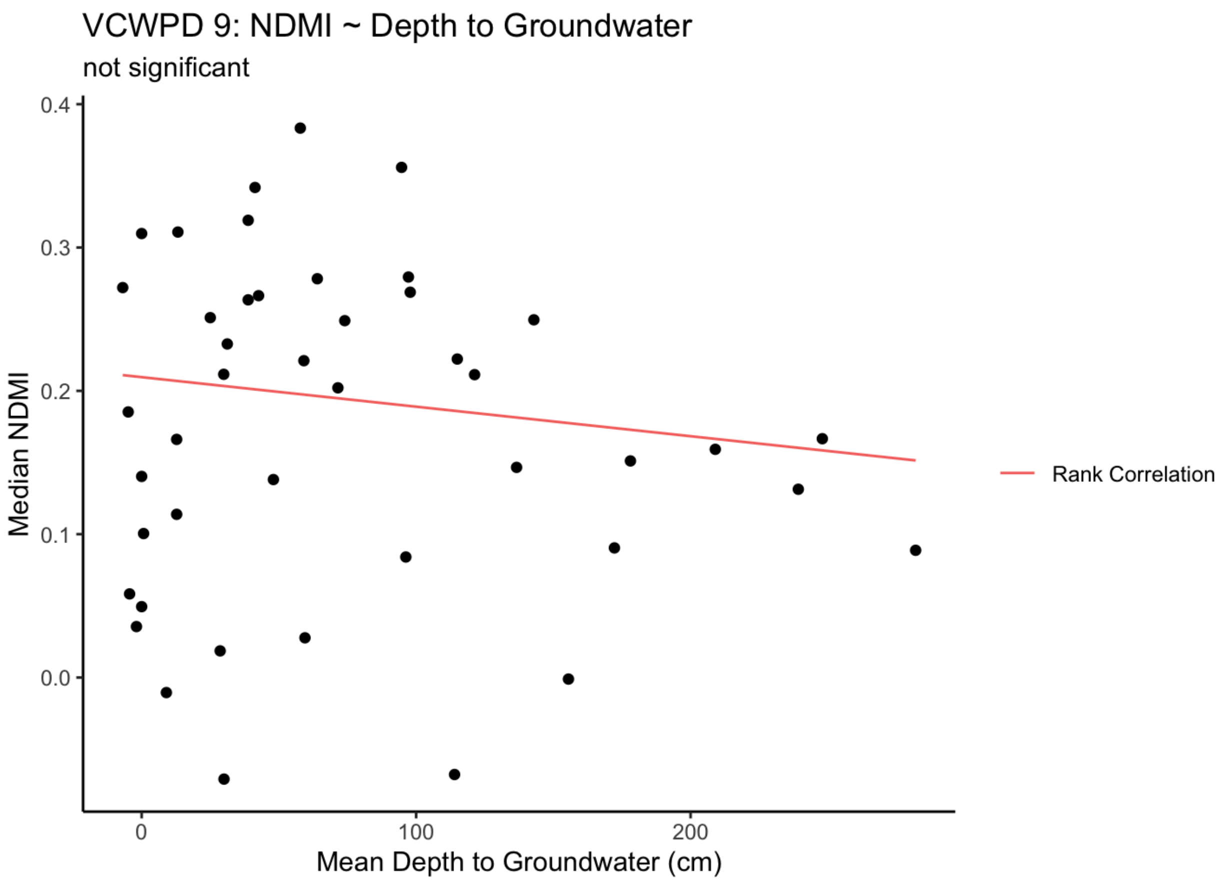
VCWPD 9 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc9)
##
## Coefficients:
##              Estimate Std. Error t.value   p.value
## (Intercept) 4.8113e-01 3.7640e-02 12.7823 4.562e-16 ***
## mean_dtg    9.5552e-05 2.9091e-04  0.3285    0.7442
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.002277554
## Reduction in Dispersion Test: 0.09588 p-value: 0.75837
```



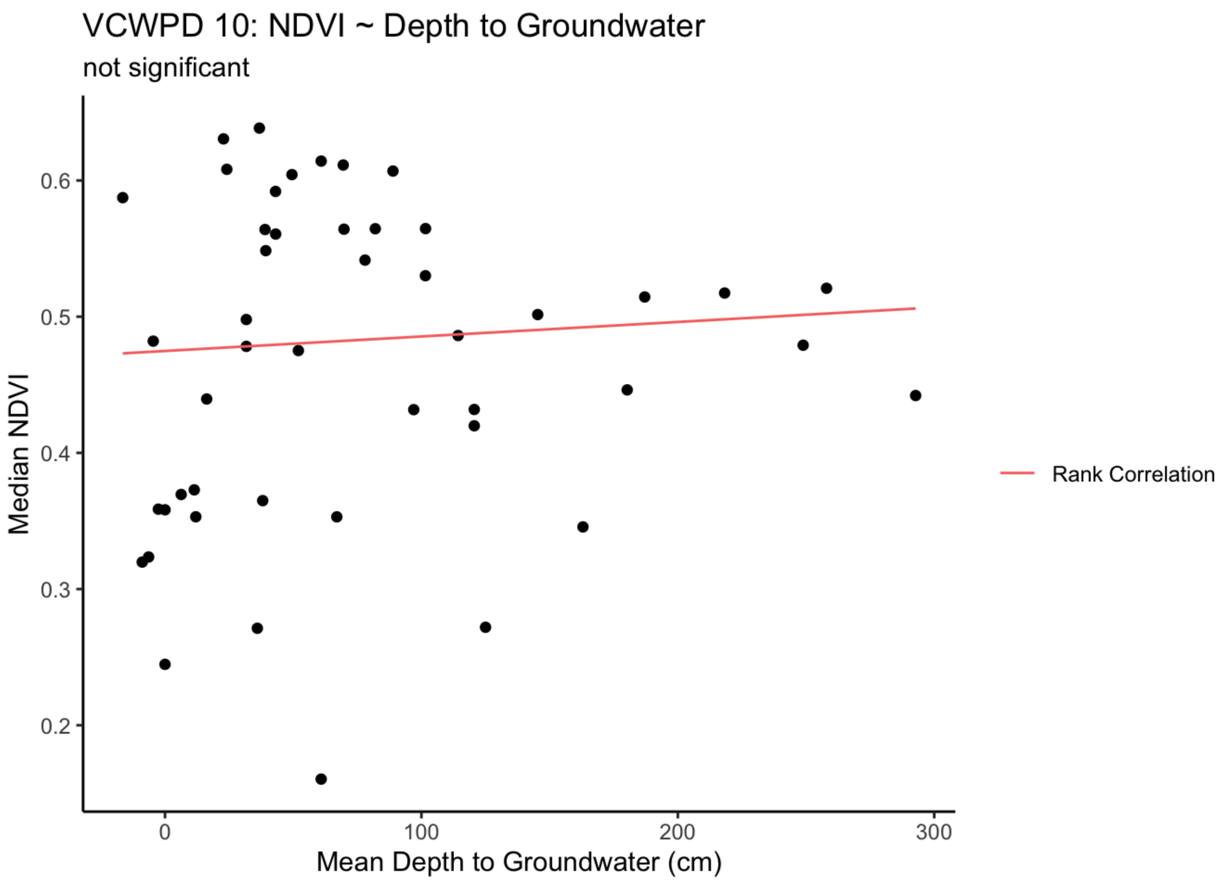
VCWPD 9 NDMI

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc9)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.20956616  0.03525329  5.9446 4.772e-07 ***
## mean_dtg    -0.00020604  0.00027161 -0.7586    0.4523
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.01450608
## Reduction in Dispersion Test: 0.61822 p-value: 0.43612
```



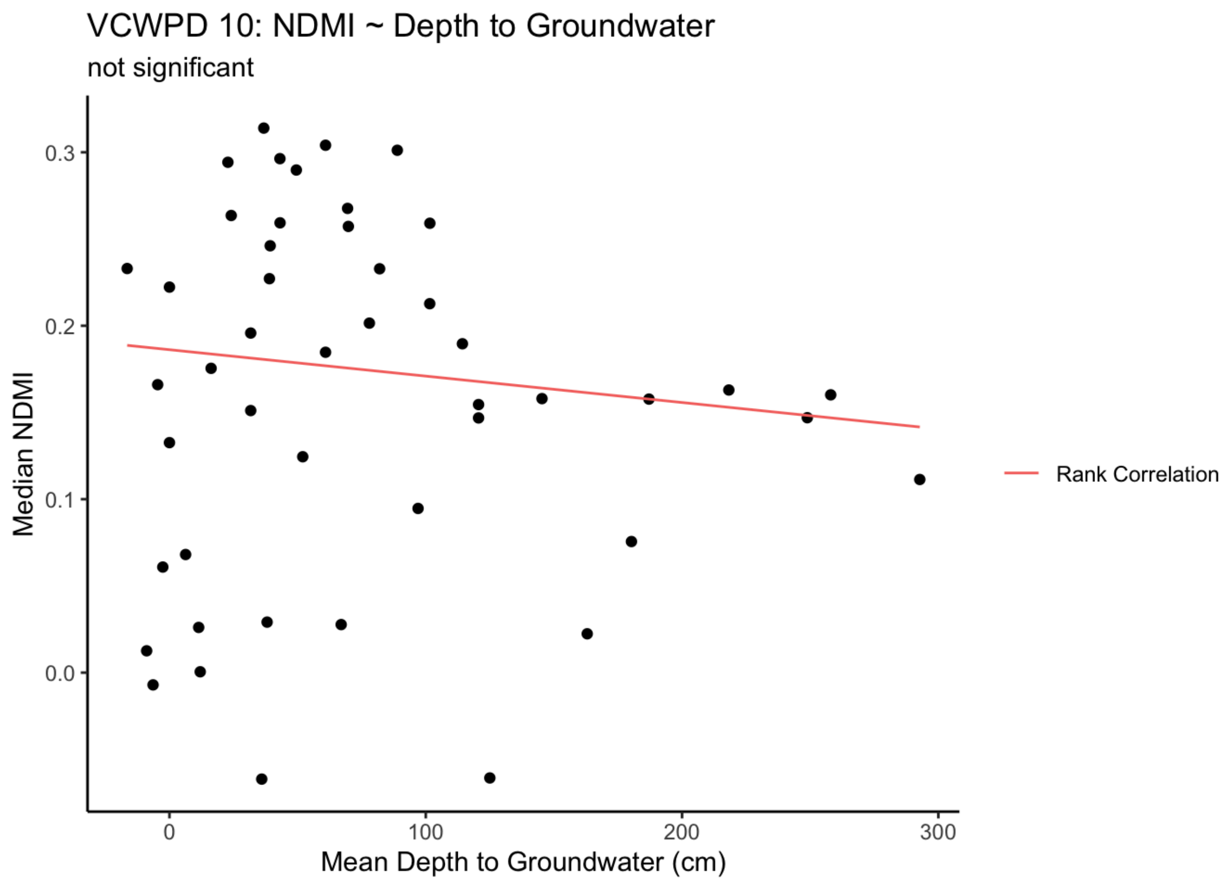
VCWPD 10 NDVI

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc10)
##
## Coefficients:
##             Estimate Std. Error t.value p.value
## (Intercept) 0.47481008 0.03273687  14.504  <2e-16 ***
## mean_dtg    0.00010651 0.00025605   0.416  0.6794
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.003560883
## Reduction in Dispersion Test: 0.16081 p-value: 0.69031
```



VCWPD 10 NDMI

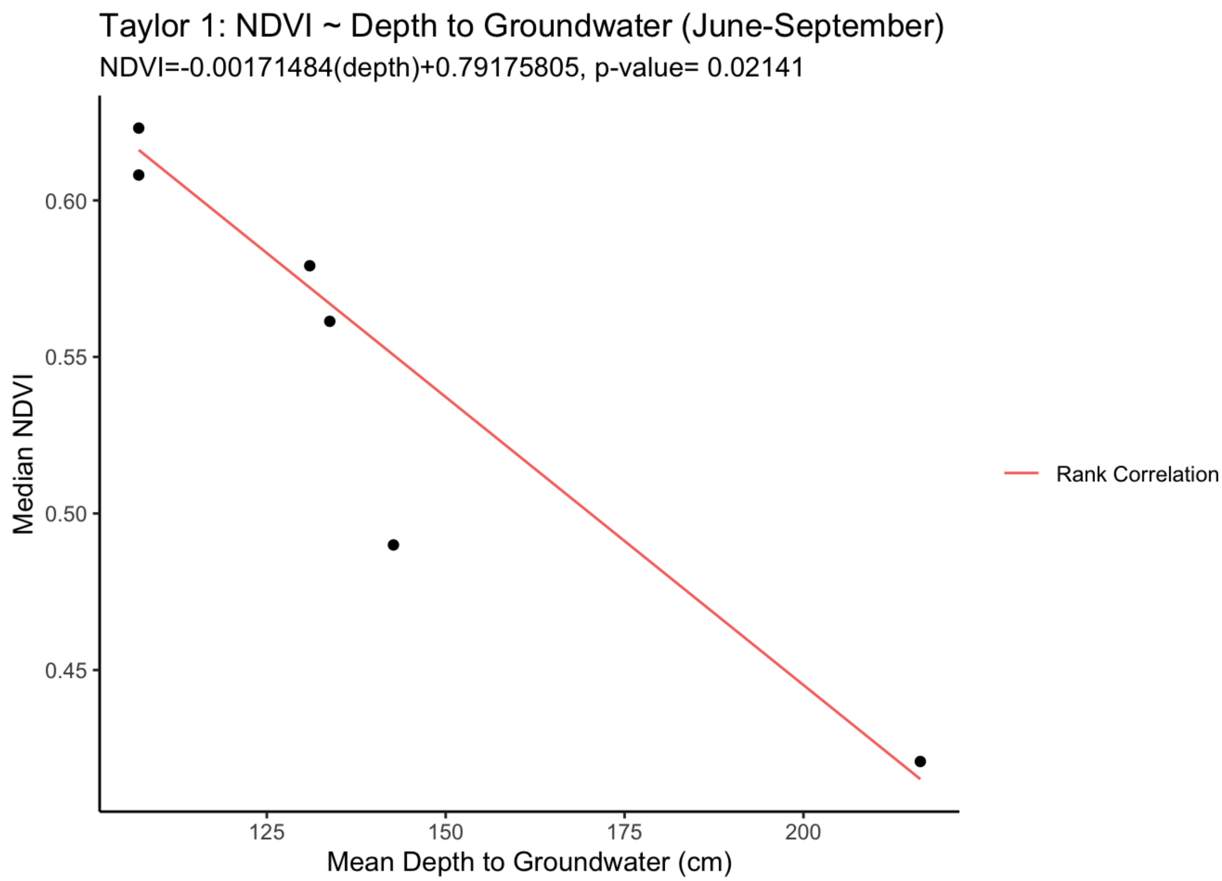
```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc10)
##
## Coefficients:
##              Estimate  Std. Error t.value  p.value
## (Intercept)  0.18618867  0.02399436  7.7597 7.73e-10 ***
## mean_dtg    -0.00015223  0.00021771 -0.6992    0.488
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.009826298
## Reduction in Dispersion Test: 0.44657 p-value: 0.50738
```



C. Summer Isolated

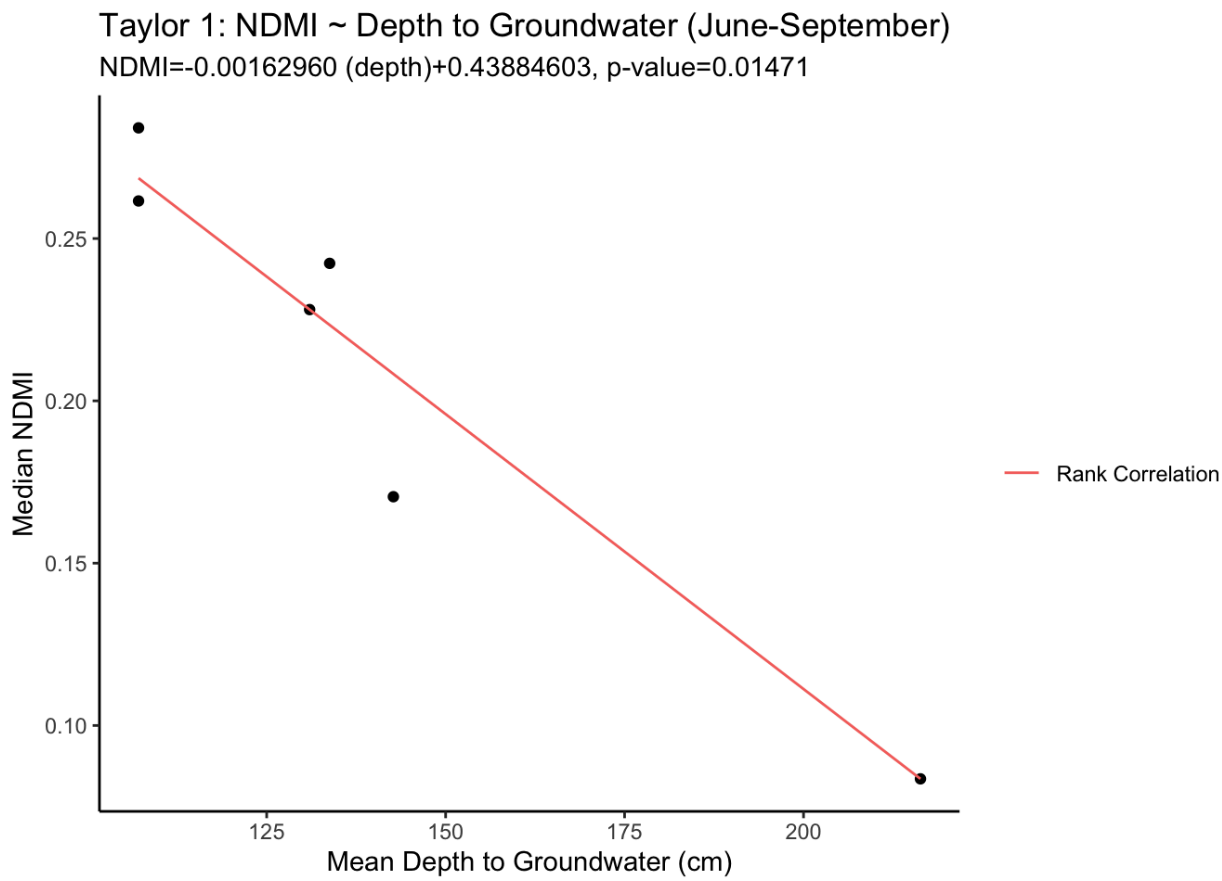
Taylor 1

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_taylor1_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.81314119  0.04485308 18.1290 5.444e-05 ***
## mean_dtg    -0.00183967  0.00026942 -6.8282  0.002406 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.8656585
## Reduction in Dispersion Test: 25.77487 p-value: 0.0071
```



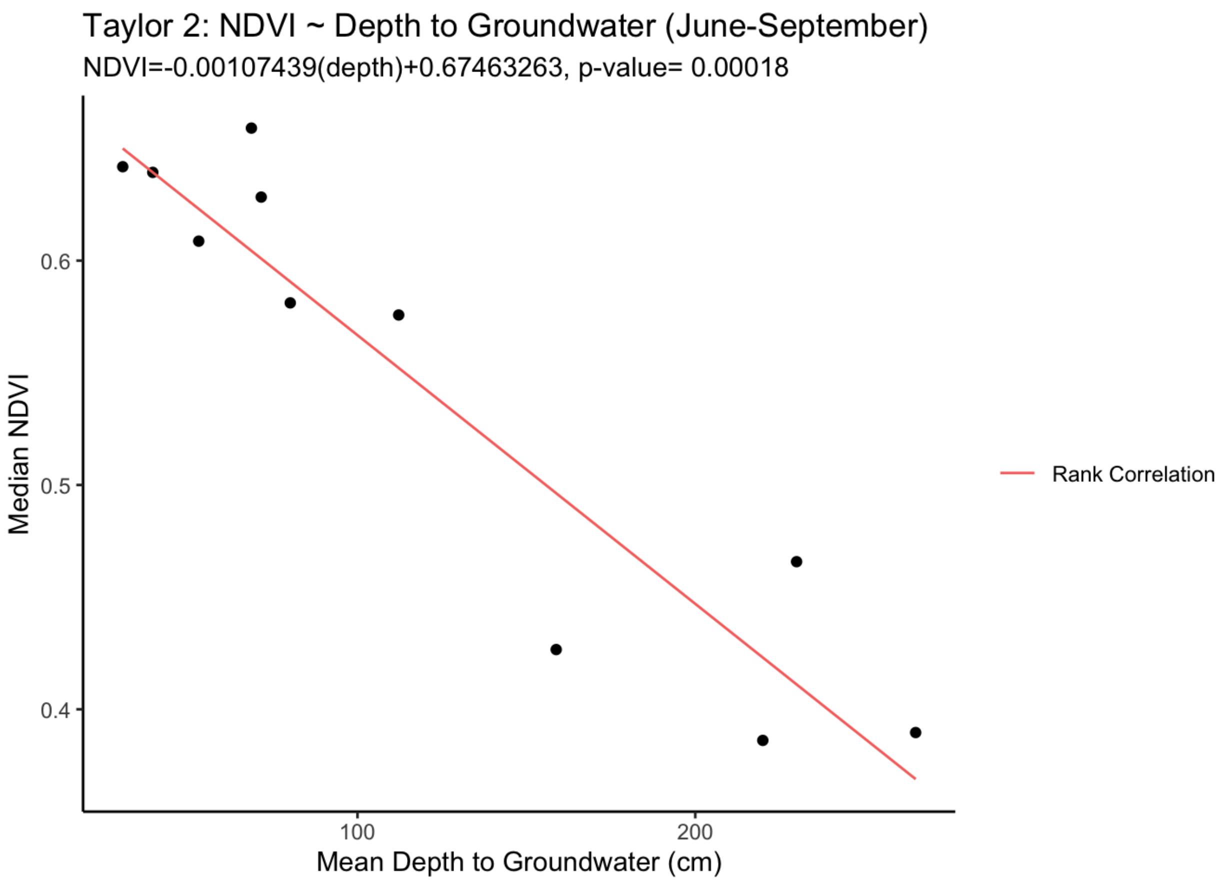
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_taylor1_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value  p.value
## (Intercept)  0.45001338  0.06743728  6.6731 0.002621 **
## mean_dtg    -0.00169391  0.00045999 -3.6825 0.021158 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7816976
## Reduction in Dispersion Test: 14.3232 p-value: 0.01936
```



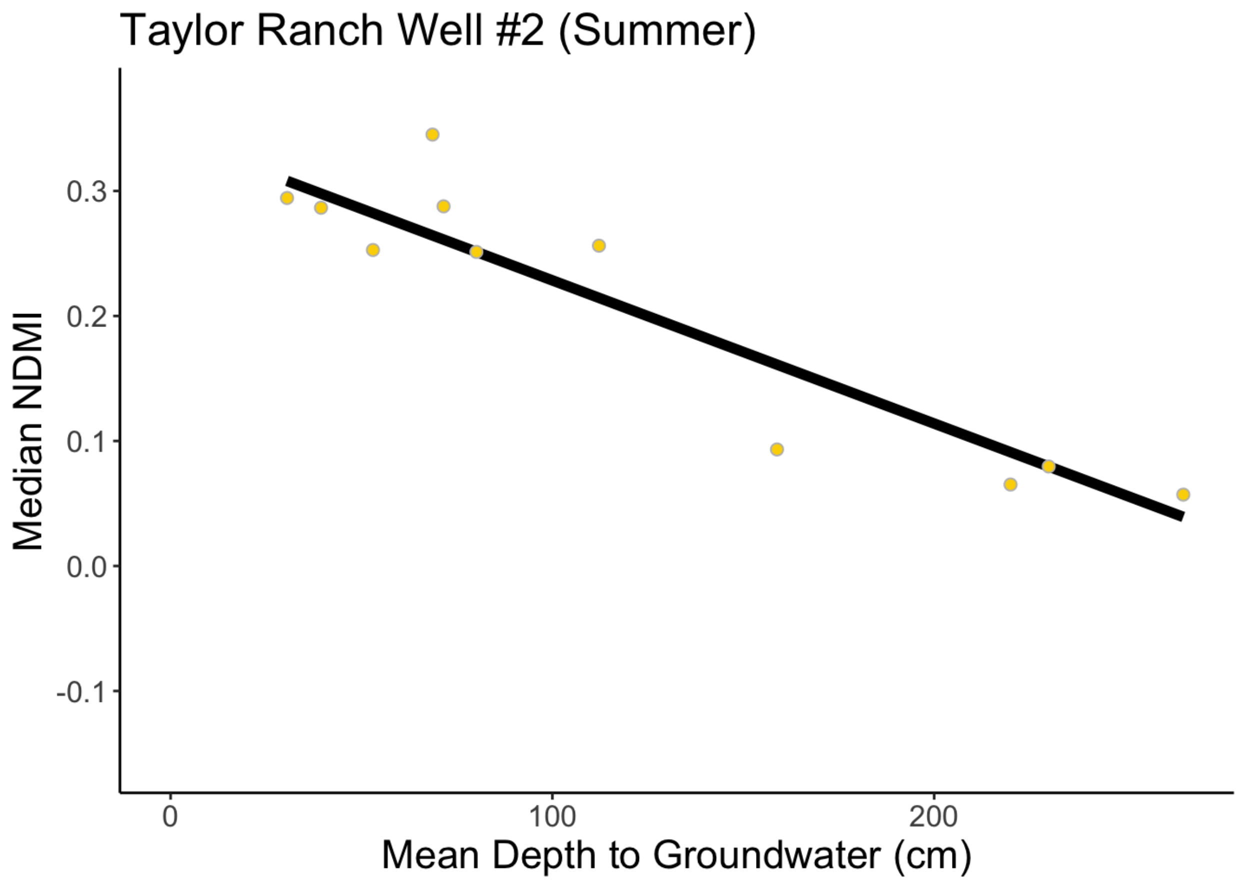
Taylor 2

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_taylor2_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.68652283  0.04122479  16.653 4.536e-08 ***
## mean_dtg    -0.00119744  0.00025477  -4.700   0.00112 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7012313
## Reduction in Dispersion Test: 21.12363 p-value: 0.0013
```



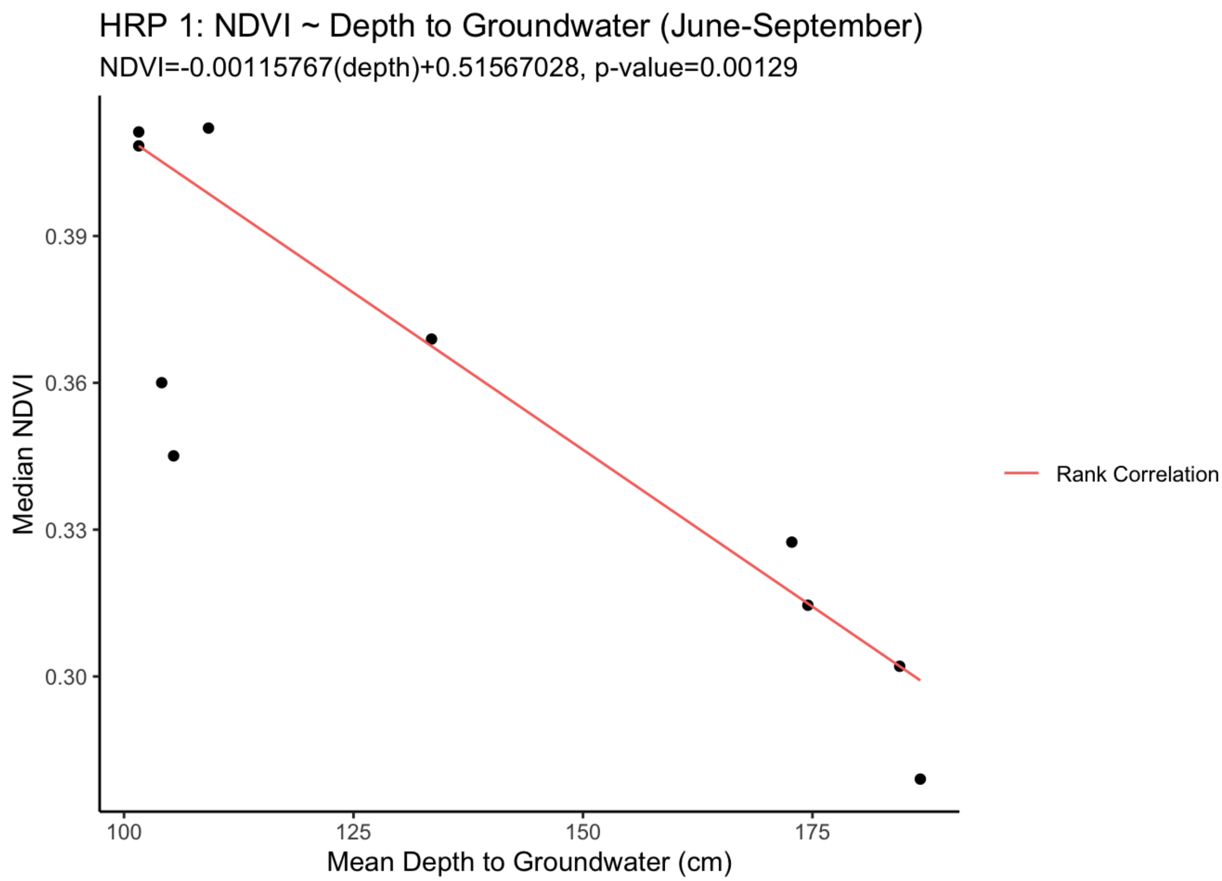
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_taylor2_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.34298705  0.03089821 11.1005 1.491e-06 ***
## mean_dtg    -0.00114519  0.00018512 -6.1863 0.0001615 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7595849
## Reduction in Dispersion Test: 28.43526 p-value: 0.00047
```

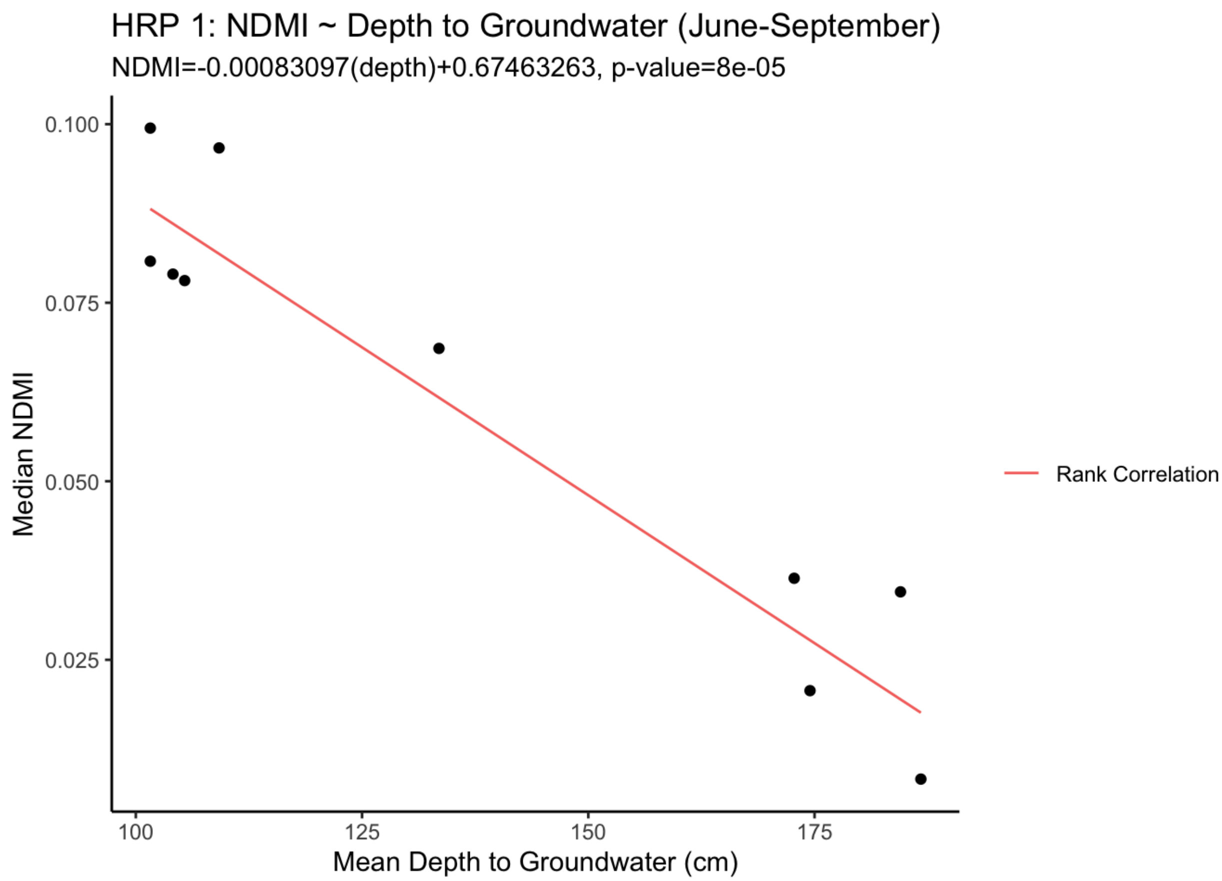


hrp1

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp1_summer)
##
## Coefficients:
##              Estimate Std. Error t.value   p.value
## (Intercept)  0.5387431  0.0307032  17.547 1.136e-07 ***
## mean_dtg    -0.0012827  0.0001865  -6.878 0.0001273 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.753826
## Reduction in Dispersion Test: 24.49735 p-value: 0.00112
```

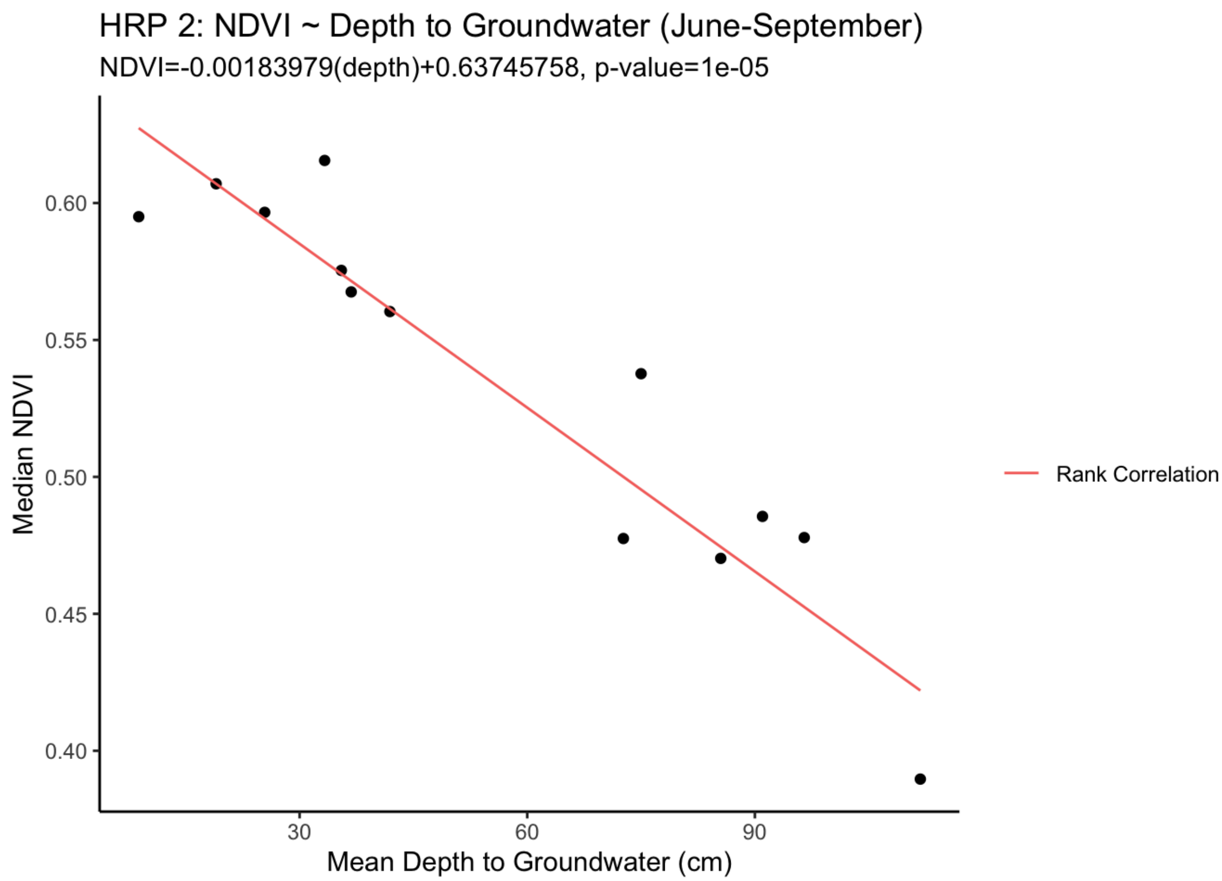



```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp1_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.17231478  0.01654507 10.4149 6.261e-06 ***
## mean_dtg    -0.00082850  0.00010992 -7.5372 6.689e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.8148262
## Reduction in Dispersion Test: 35.20265 p-value: 0.00035
```



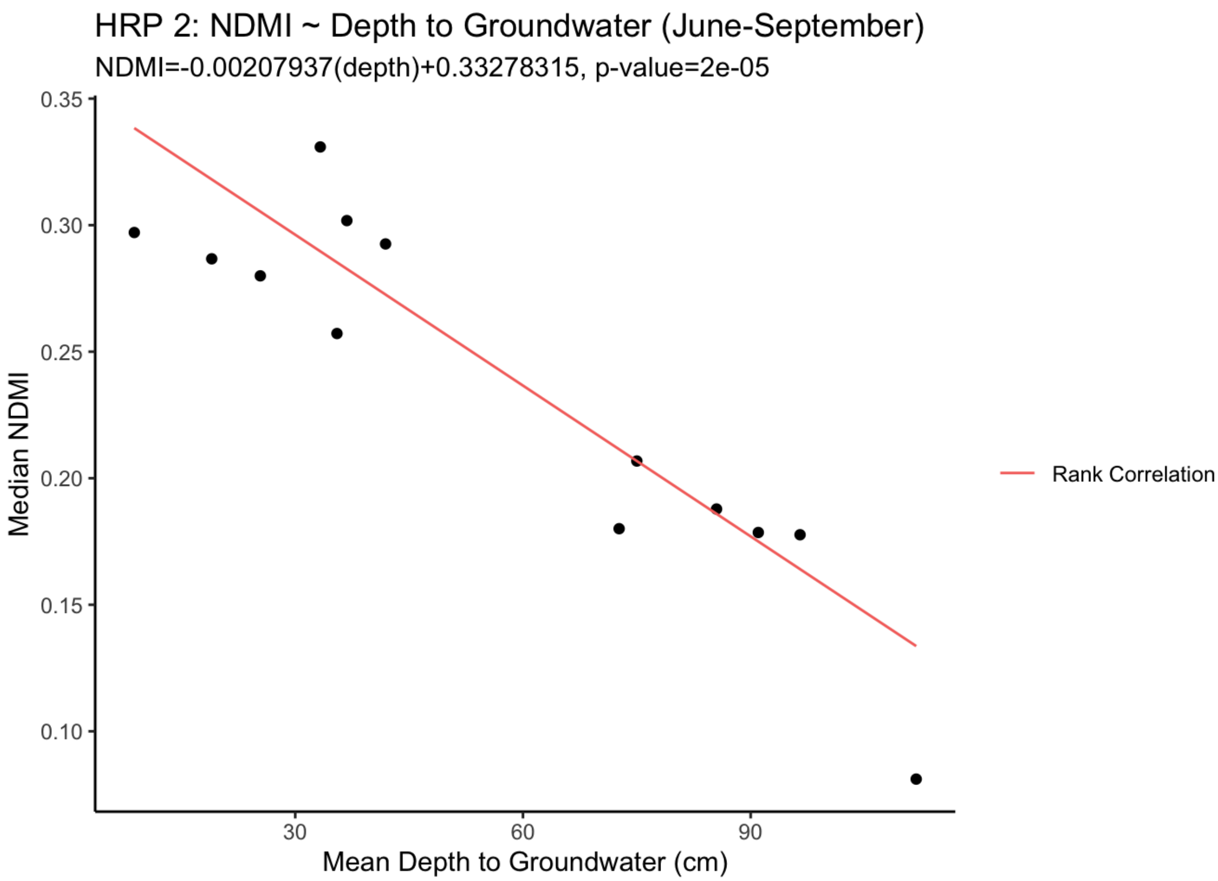
hrp2

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp2_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.64489783  0.01920386 33.5817 1.952e-12 ***
## mean_dtg    -0.00199366  0.00023456 -8.4995 3.656e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7868273
## Reduction in Dispersion Test: 40.60135 p-value: 5e-05
```



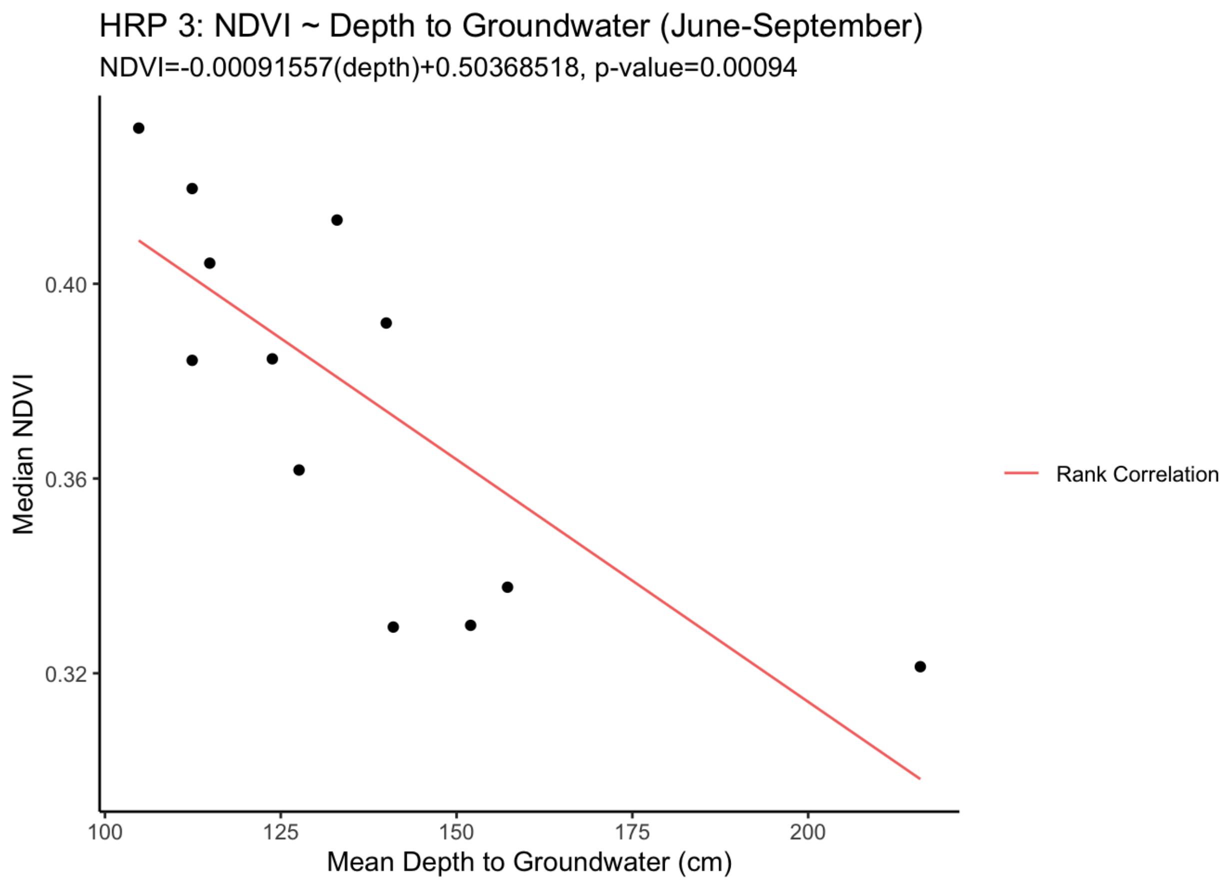
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp2_summer)
##
## Coefficients:
##              Estimate Std. Error t.value   p.value
## (Intercept)  0.3558380  0.0230331 15.4490 8.352e-09 ***
## mean_dtg    -0.0019872  0.0003147 -6.3145 5.720e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.724204
## Reduction in Dispersion Test: 28.88456 p-value: 0.00023
```

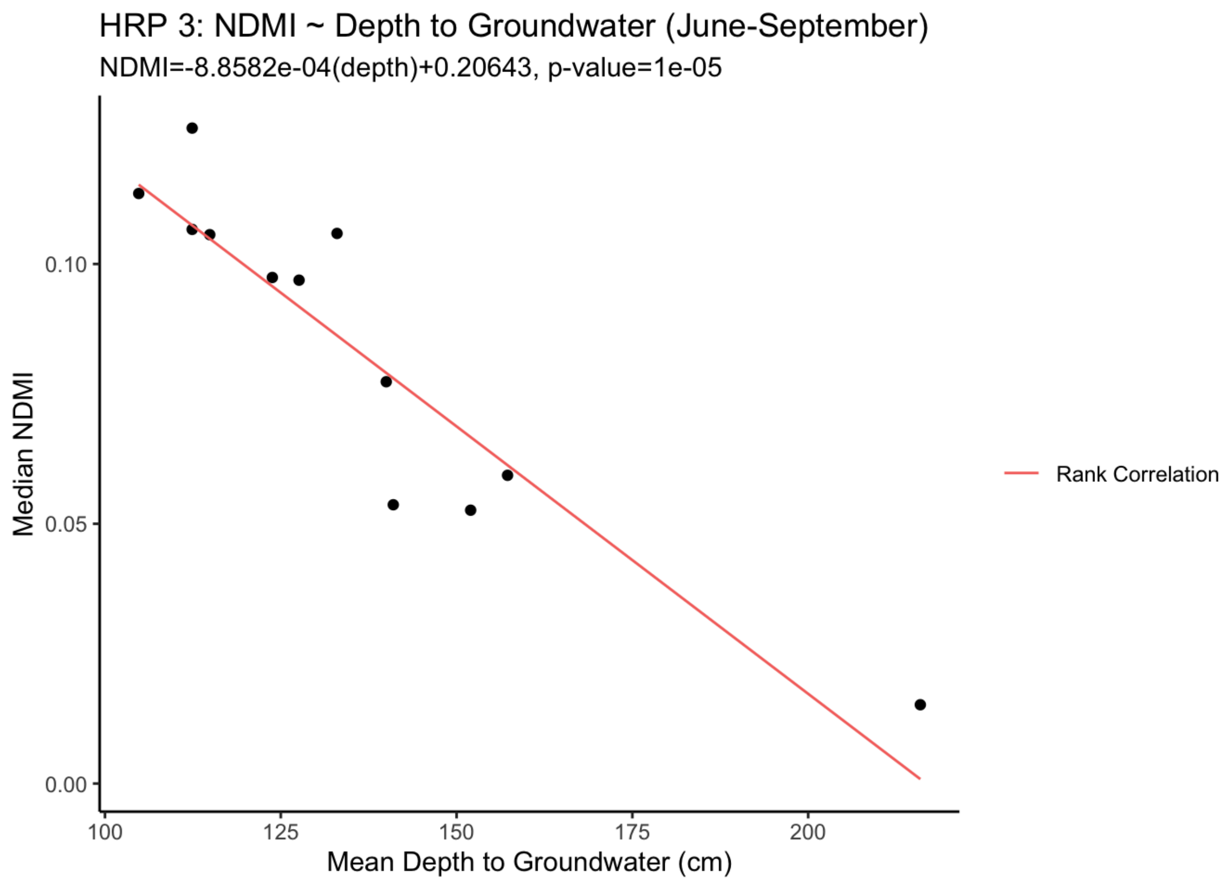


hrp3

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp3_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.51320095  0.04244039 12.0923 2.718e-07 ***
## mean_dtg    -0.00099530  0.00029403 -3.3851  0.006943 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.5245097
## Reduction in Dispersion Test: 11.03092 p-value: 0.00773
```

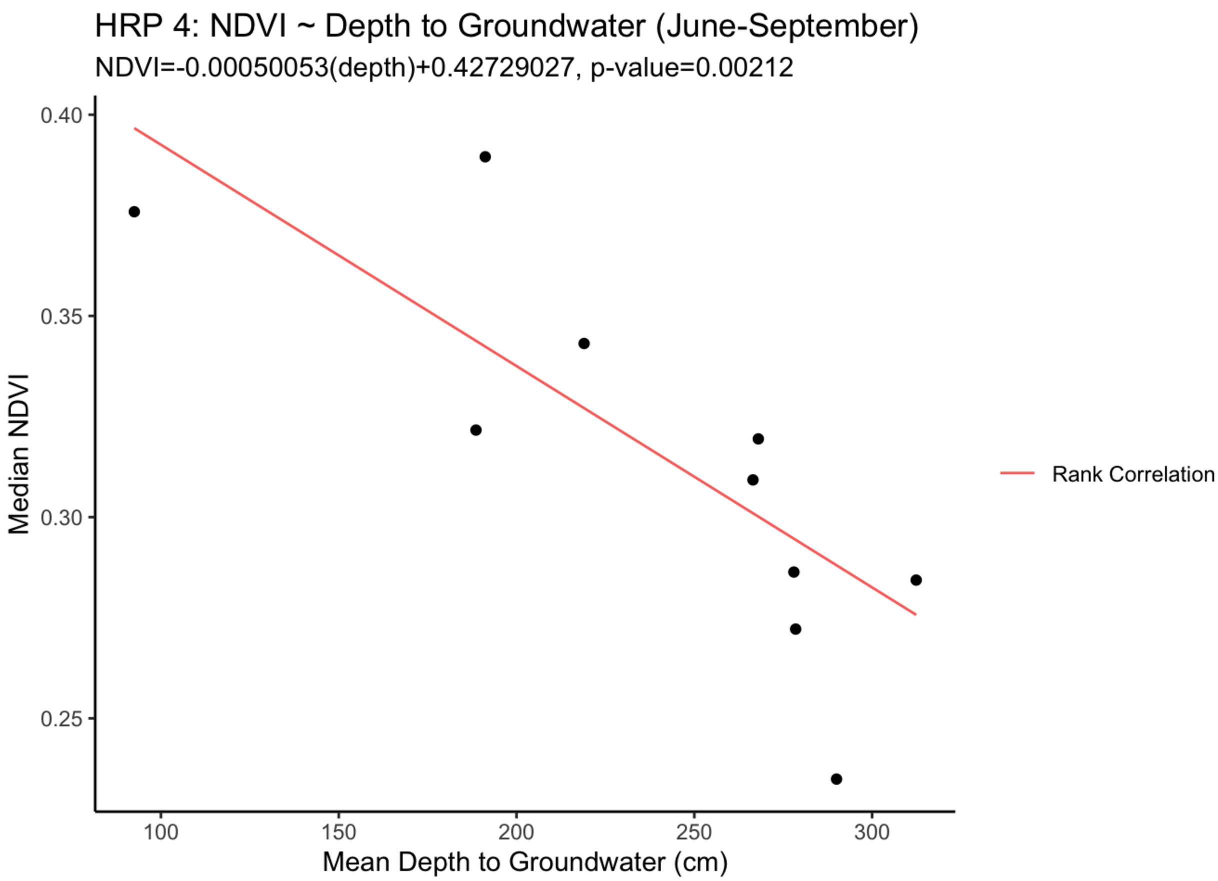



```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp3_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.22312554  0.01855366  12.026 2.863e-07 ***
## mean_dtg    -0.00102924  0.00013155  -7.824 1.430e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.777862
## Reduction in Dispersion Test: 35.01706 p-value: 0.00015
```



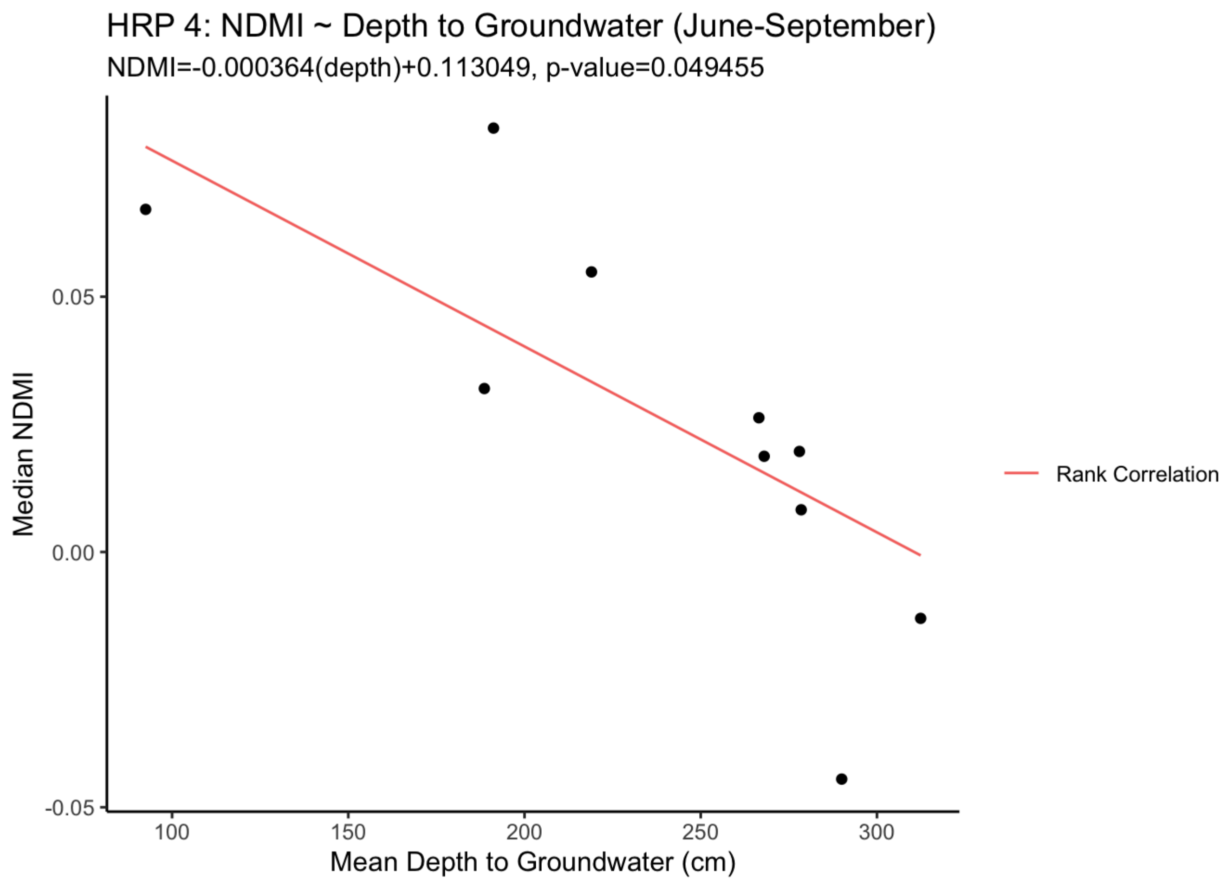
hrp4

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp4_summer)
##
## Coefficients:
##                Estimate  Std. Error t.value   p.value
## (Intercept)  0.44755253  0.04885603  9.1606 1.627e-05 ***
## mean_dtg    -0.00055005  0.00019789 -2.7796   0.02394 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.5470251
## Reduction in Dispersion Test: 9.66102 p-value: 0.01448
```



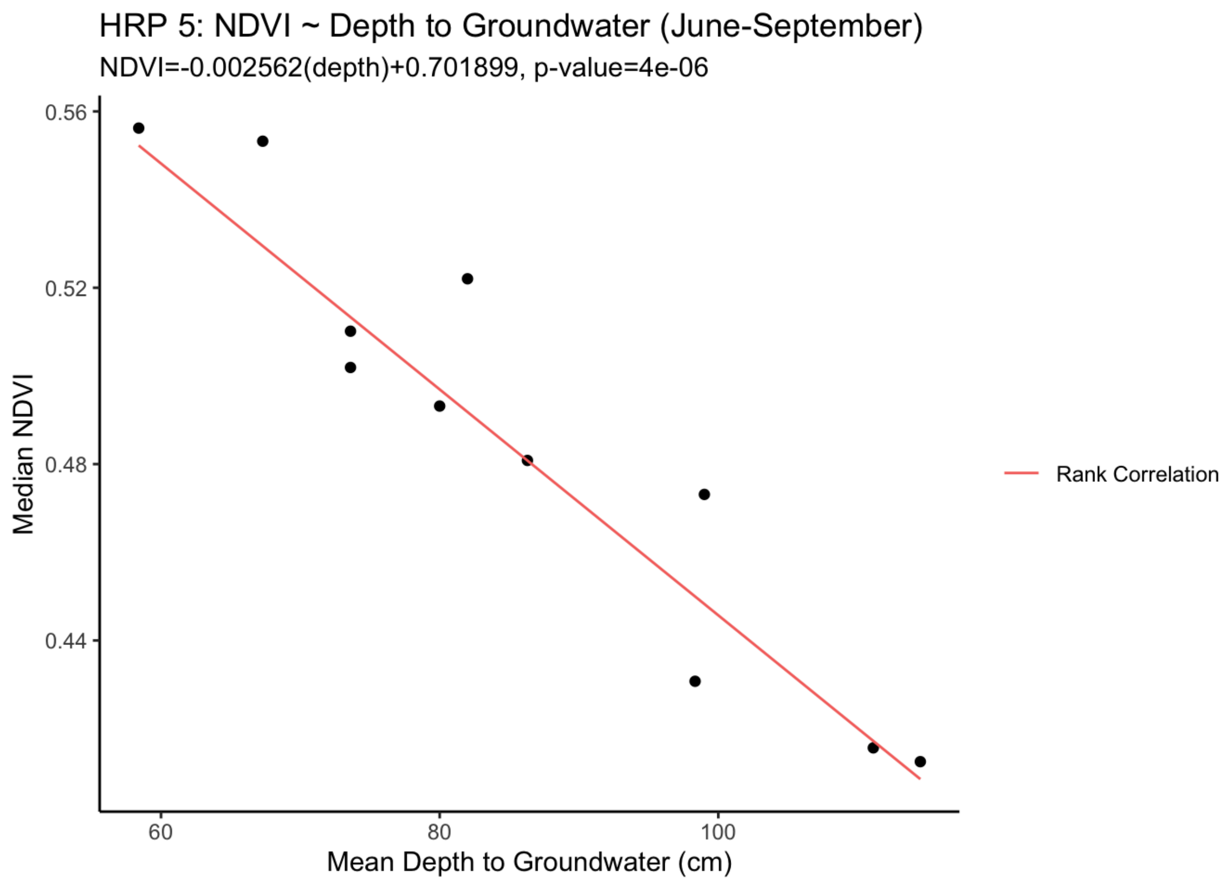
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp4_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  0.11304874  0.03895476  2.9021 0.01983 *
## mean_dtg    -0.00036428  0.00015749 -2.3130 0.04945 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.5217081
## Reduction in Dispersion Test: 8.72619 p-value: 0.01831
```



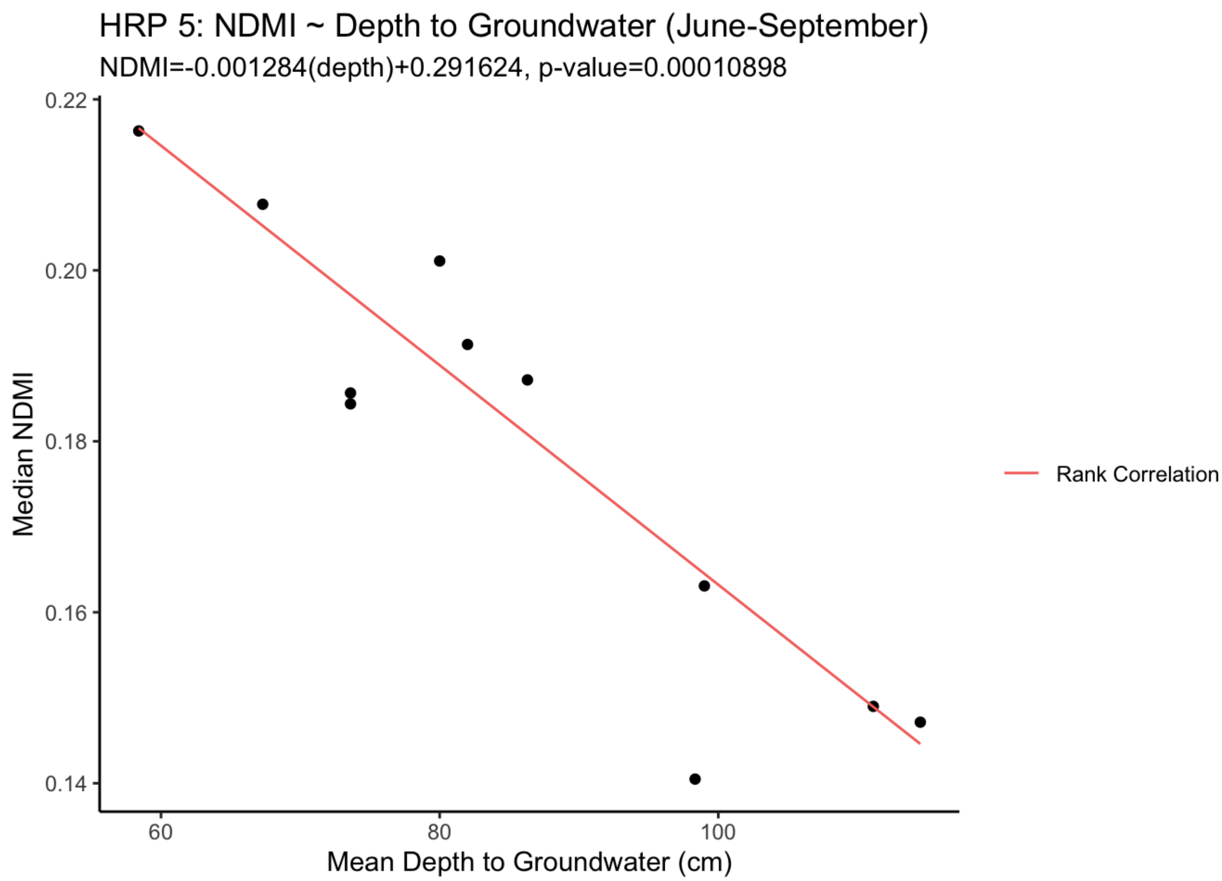
hrp5

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp5_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.70189859  0.02492734 28.1578 4.369e-10 ***
## mean_dtg    -0.00256163  0.00026146 -9.7973 4.242e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.8494428
## Reduction in Dispersion Test: 50.77793 p-value: 6e-05
```



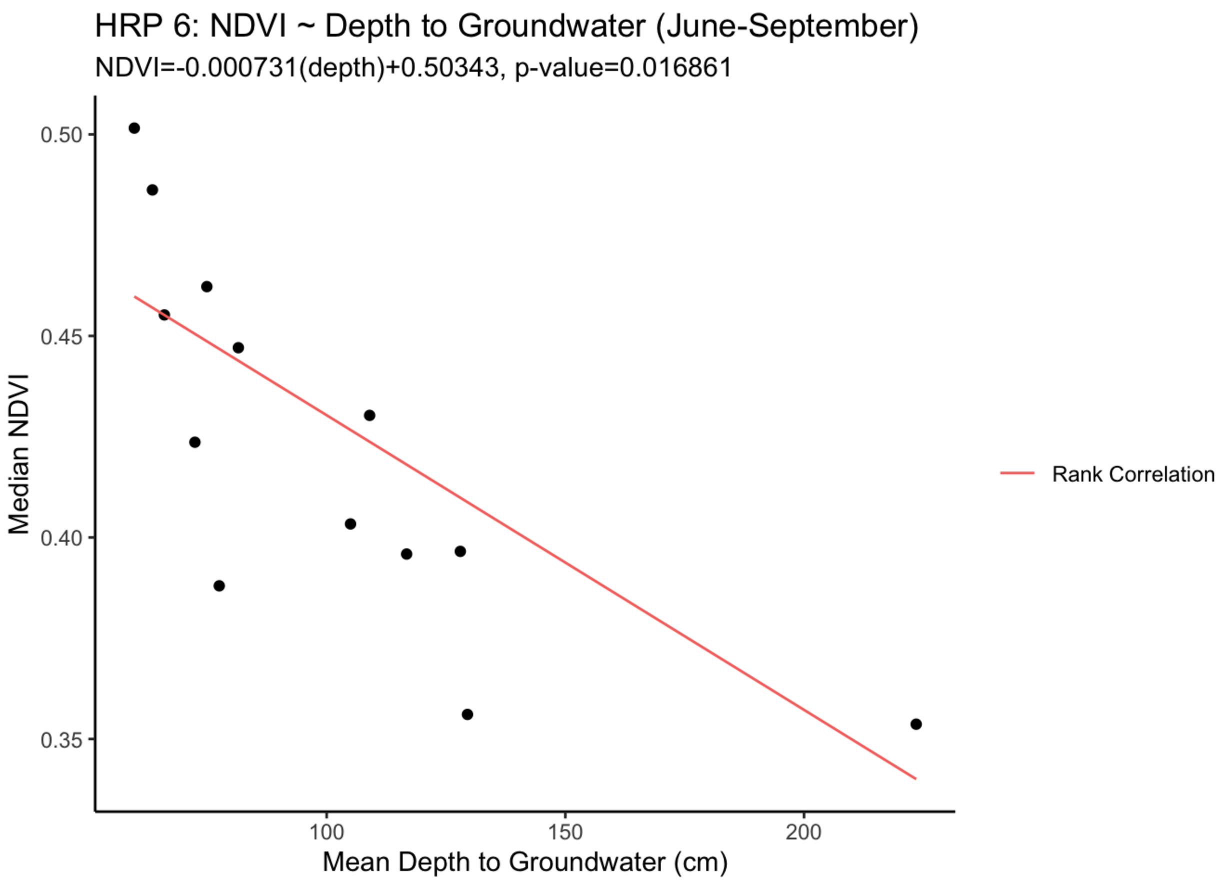
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp5_summer)
##
## Coefficients:
##             Estimate  Std. Error t.value   p.value
## (Intercept)  0.29162393  0.01783894 16.3476 5.332e-08 ***
## mean_dtg    -0.00128351  0.00019688 -6.5193  0.000109 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7714855
## Reduction in Dispersion Test: 30.38481 p-value: 0.00037
```



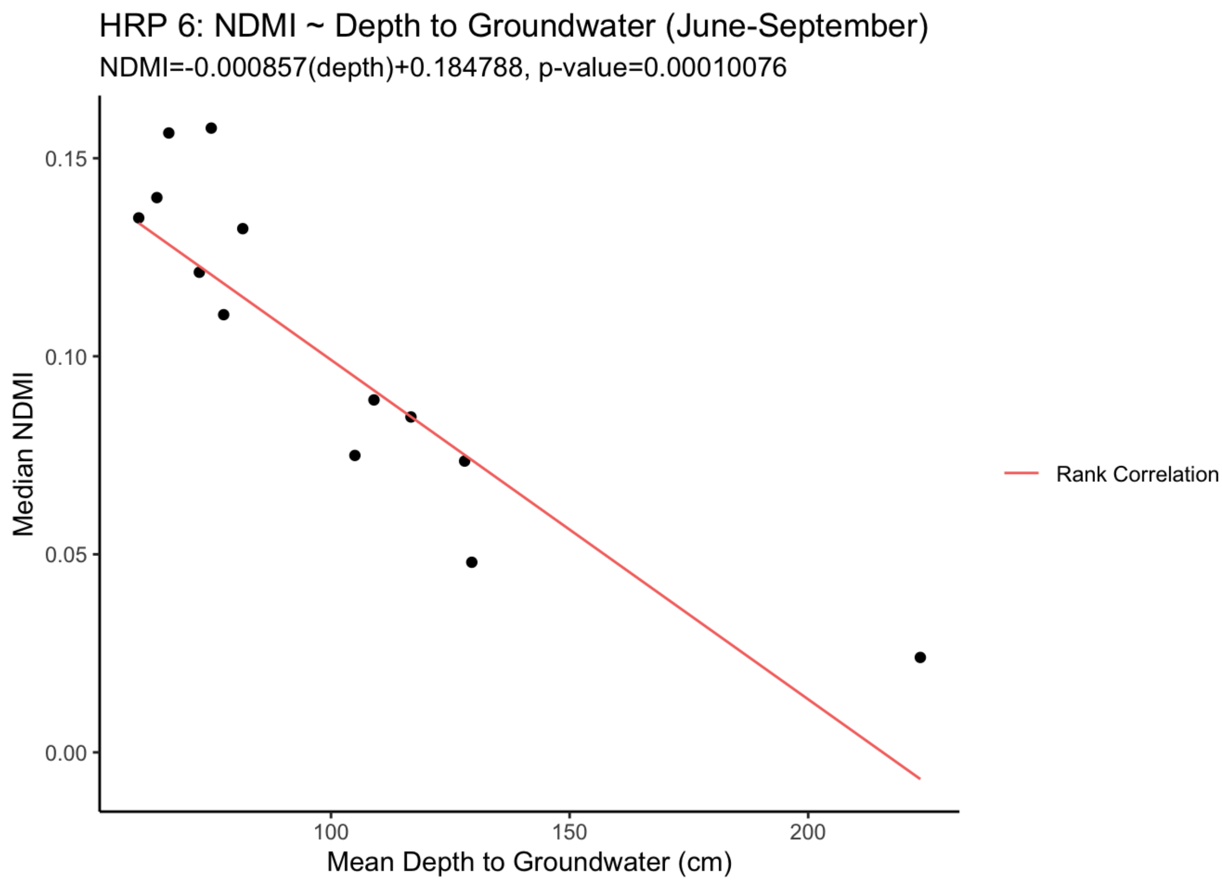
hrp6

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp6_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.50343025  0.02863658 17.5800 2.122e-09 ***
## mean_dtg    -0.00073056  0.00025966 -2.8135   0.01686 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.4967722
## Reduction in Dispersion Test: 10.85889 p-value: 0.00714
```



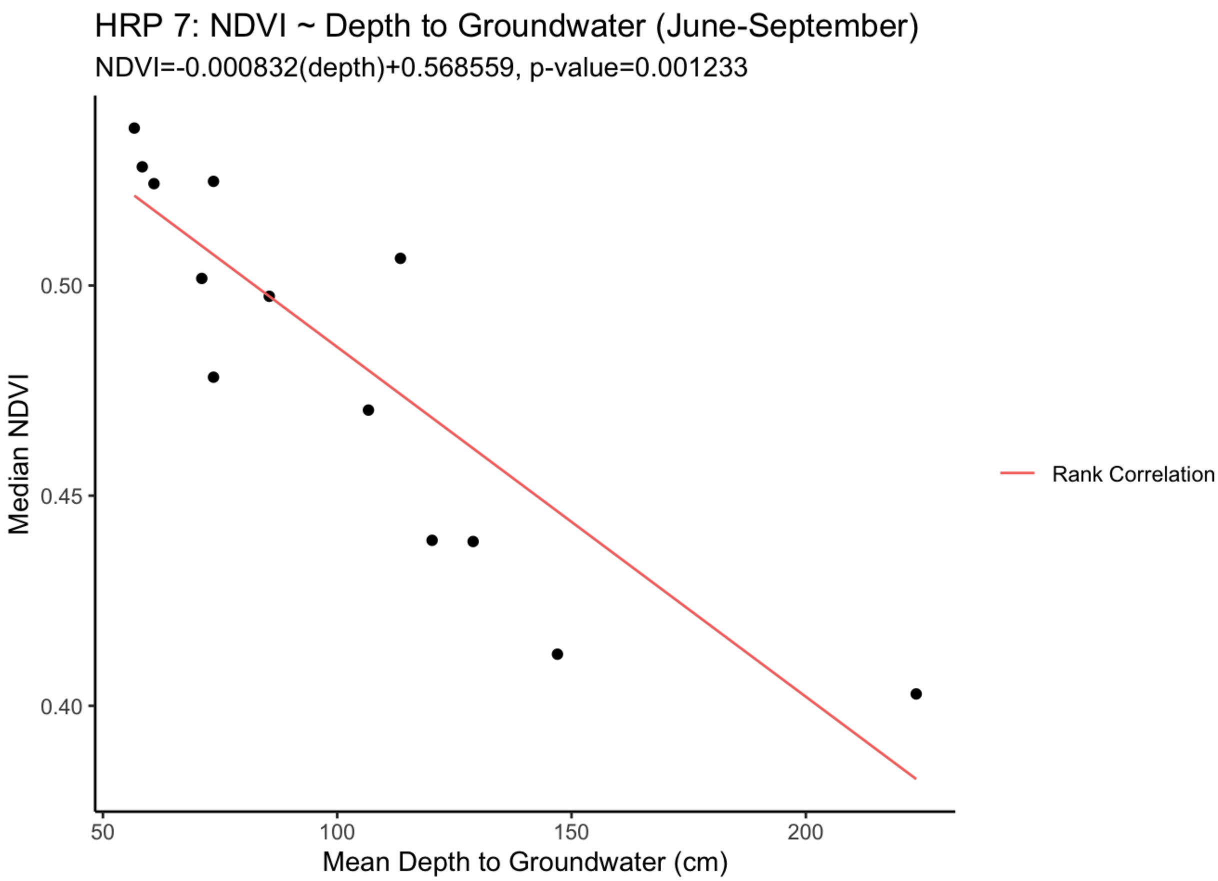
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp6_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.18478795  0.01794959  10.295 5.526e-07 ***
## mean_dtg    -0.00085749  0.00014495  -5.916 0.0001008 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7055442
## Reduction in Dispersion Test: 26.35704 p-value: 0.00033
```

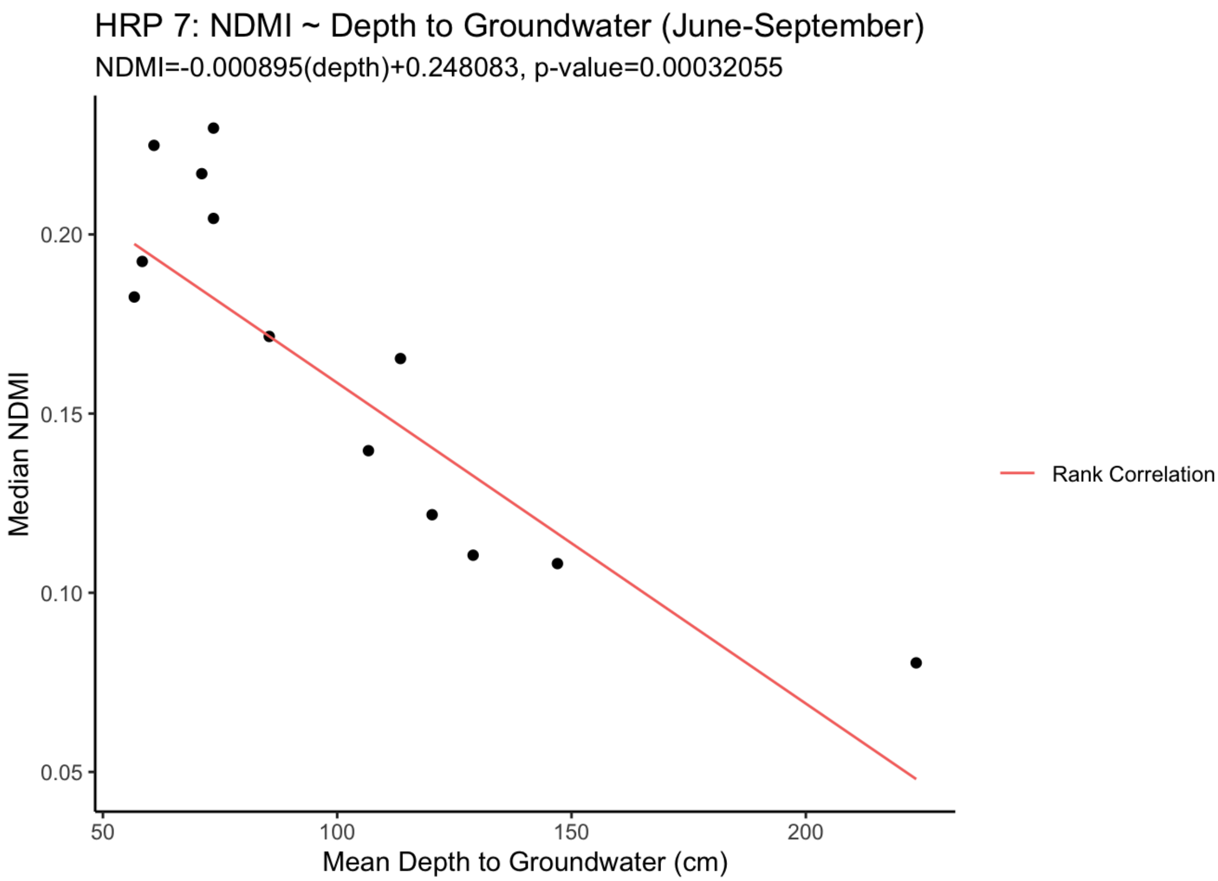


hrp7

Unset
```
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp7_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.56855915  0.02382174 23.8672 7.962e-11 ***
## mean_dtg    -0.00083186  0.00019297 -4.3109  0.001233 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6353423
## Reduction in Dispersion Test: 19.16527 p-value: 0.0011
```

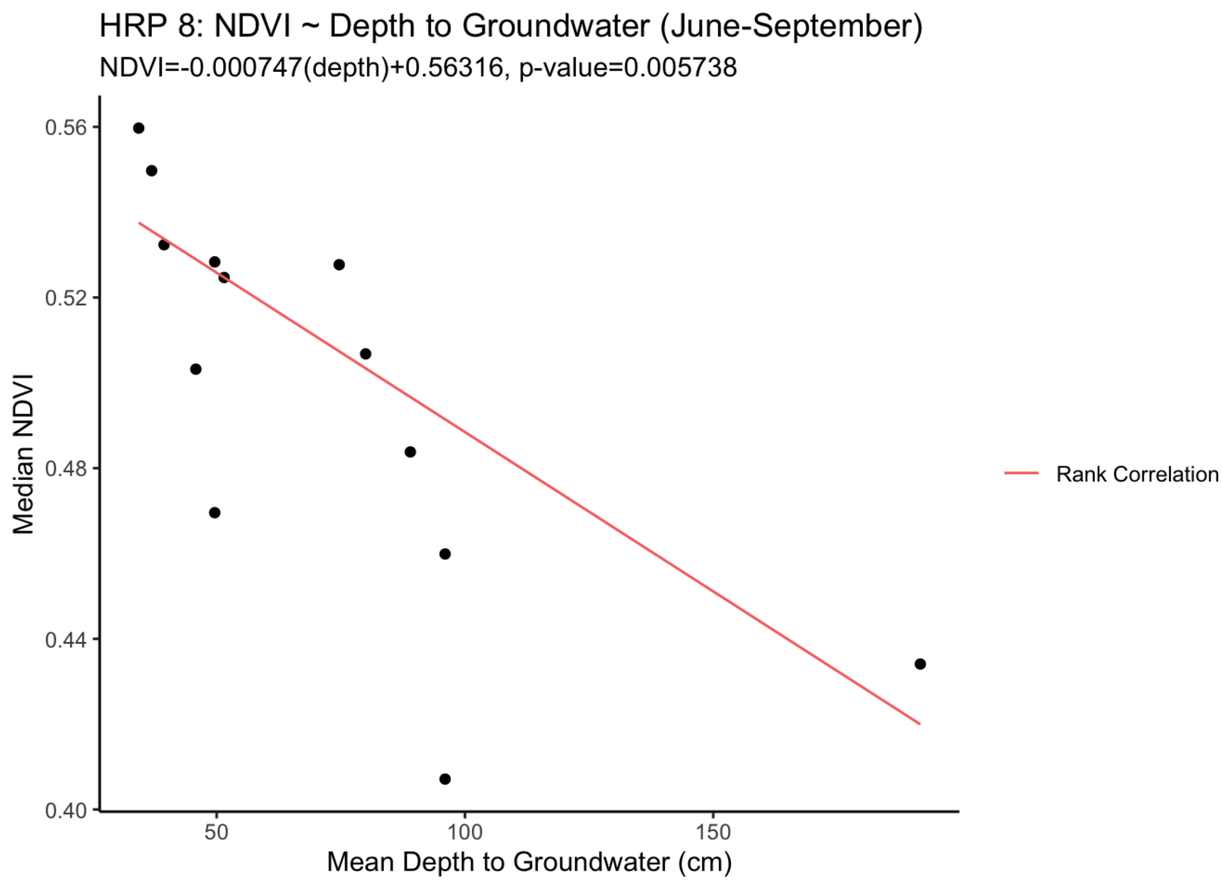



```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp7_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.24808341  0.02239265 11.0788 2.632e-07 ***
## mean_dtg    -0.00089543  0.00017403 -5.1453 0.0003206 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6806061
## Reduction in Dispersion Test: 23.44023 p-value: 0.00052
```



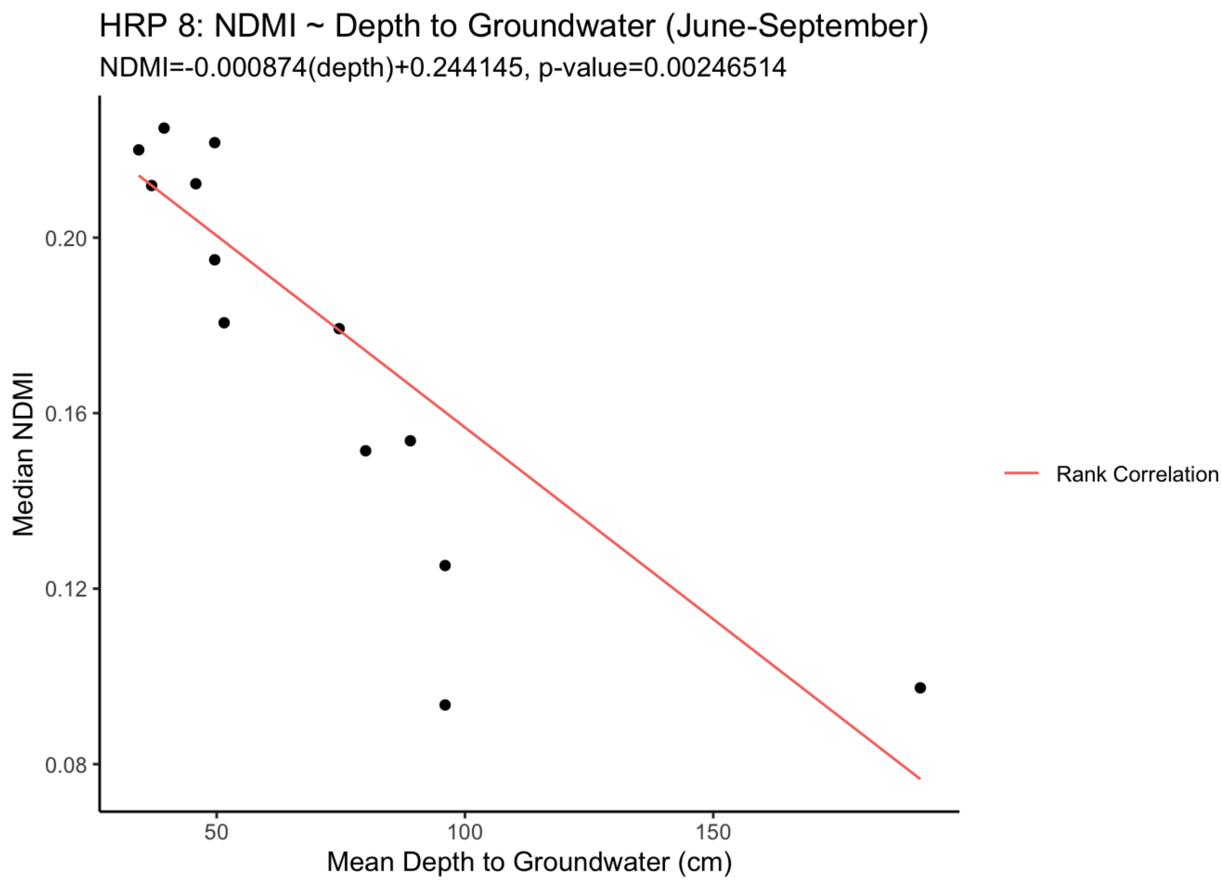
hrp8

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp8_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.56316047  0.02057545 27.3705 1.806e-11 ***
## mean_dtg    -0.00074700  0.00021852 -3.4185  0.005738 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.5259032
## Reduction in Dispersion Test: 12.20201 p-value: 0.00503
```



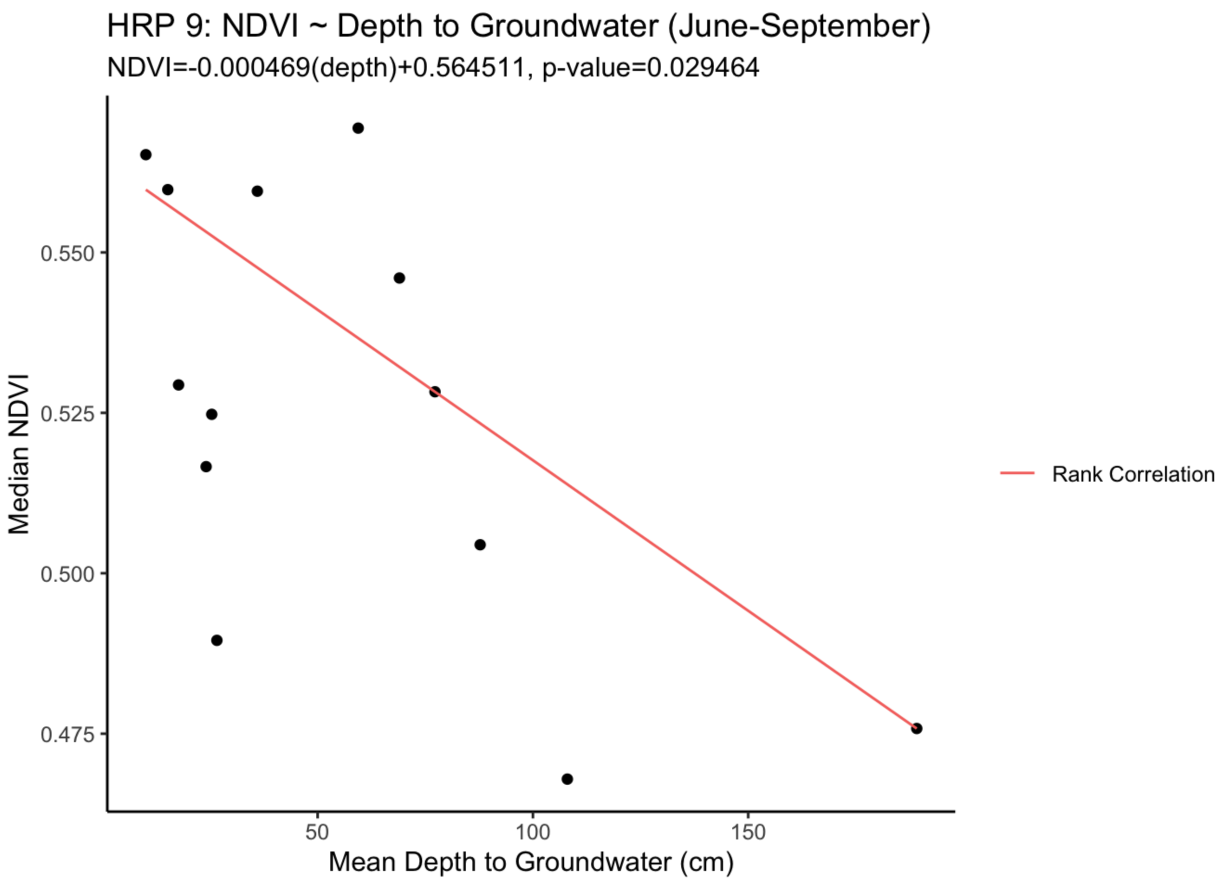
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp8_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value  p.value
## (Intercept)  0.24414520  0.01953940 12.4950 7.67e-08 ***
## mean_dtg    -0.00087443  0.00022406 -3.9027 0.002465 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6101854
## Reduction in Dispersion Test: 17.21854 p-value: 0.00162
```

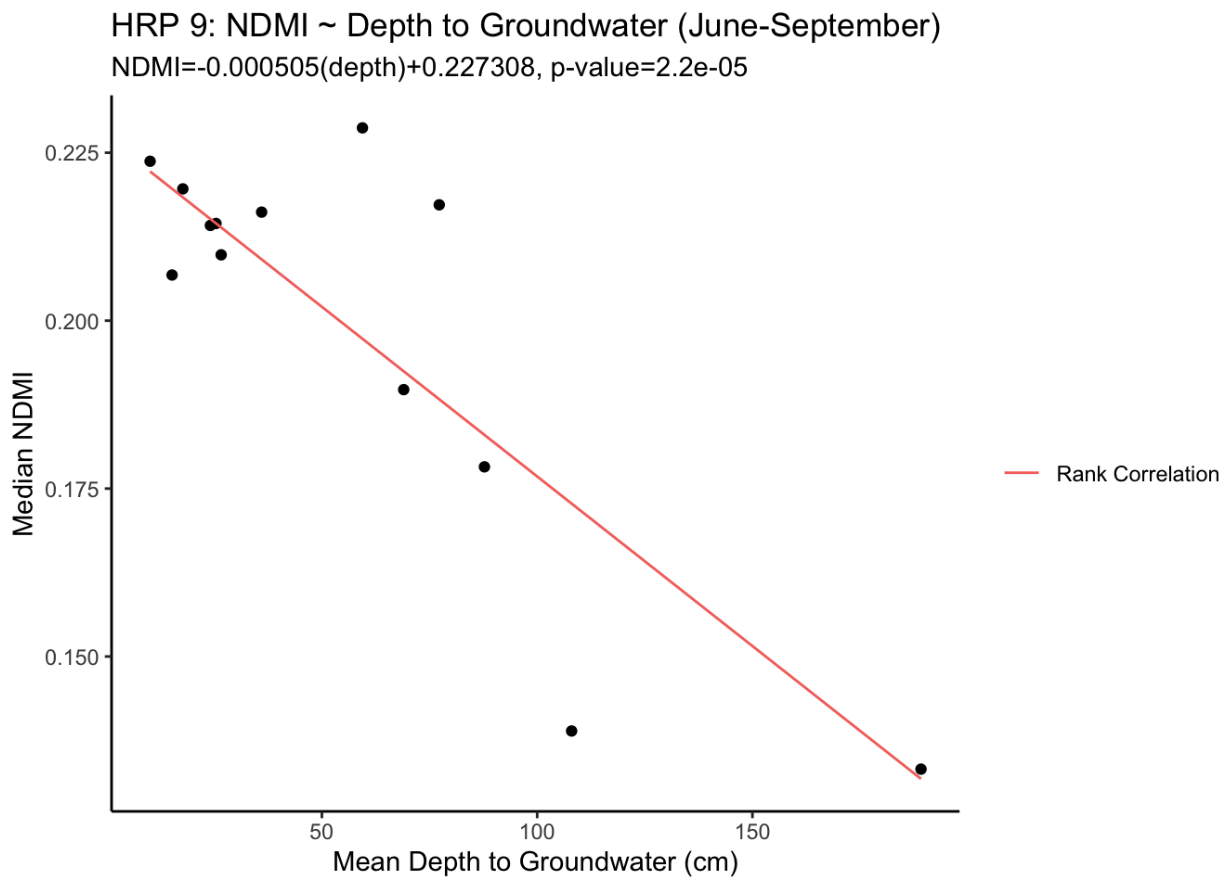


hrp9

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_hrp9_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.56451063  0.01774133 31.8190 3.513e-12 ***
## mean_dtg    -0.00046894  0.00018751 -2.5008   0.02946 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.3327002
## Reduction in Dispersion Test: 5.48435 p-value: 0.03904
```



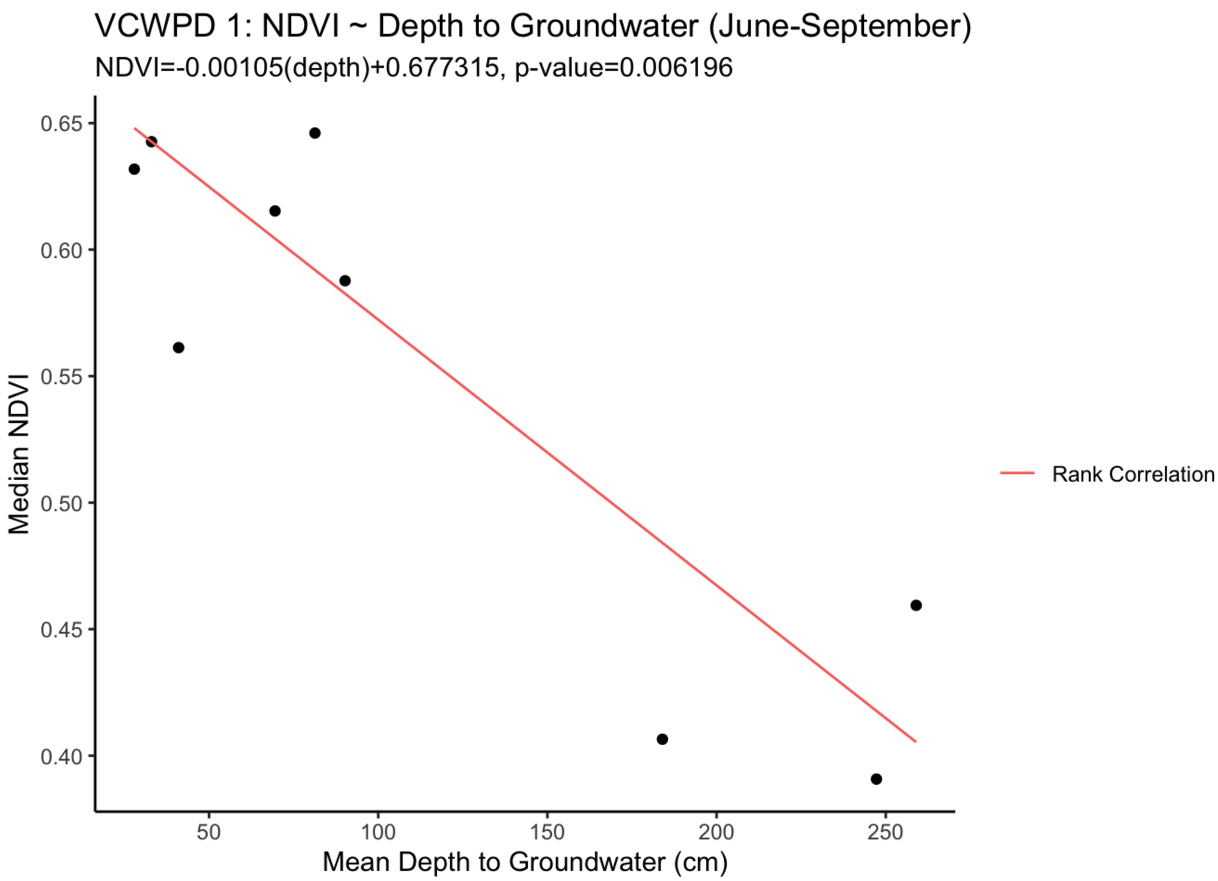

```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_hrp9_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.22730791  0.00536082  42.402 1.529e-13 ***
## mean_dtg    -0.00050545  0.00007196  -7.024 2.200e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7042292
## Reduction in Dispersion Test: 26.19096 p-value: 0.00033
```



vc1

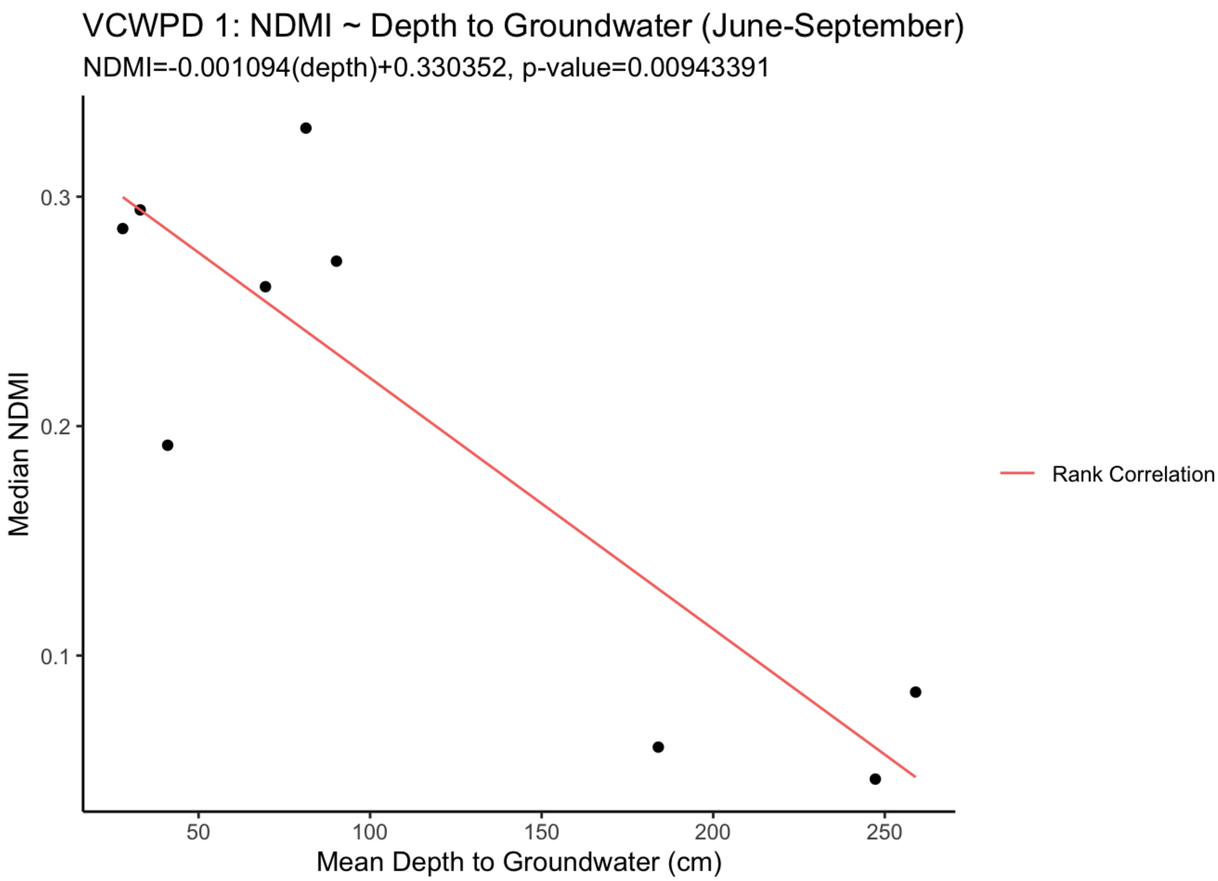
Unset

```
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc1_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.67731489  0.05052212  13.406 3.013e-06 ***
## mean_dtg    -0.00105039  0.00027198  -3.862  0.006196 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6512118
## Reduction in Dispersion Test: 13.06949 p-value: 0.00856
```



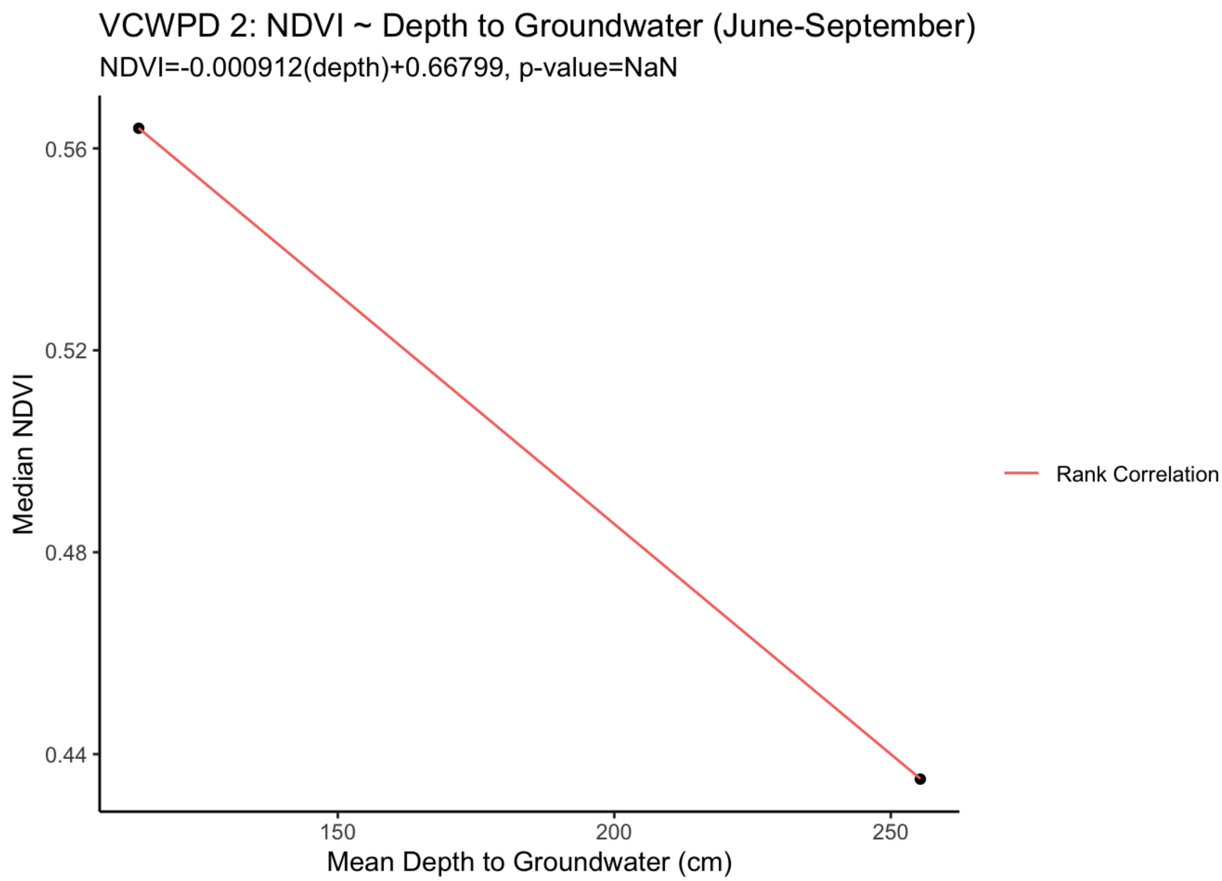
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc1_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.33035219  0.04919666  6.7149 0.0002737 ***
## mean_dtg    -0.00109387  0.00030876 -3.5428 0.0094339 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6259536
## Reduction in Dispersion Test: 11.71425 p-value: 0.0111
```



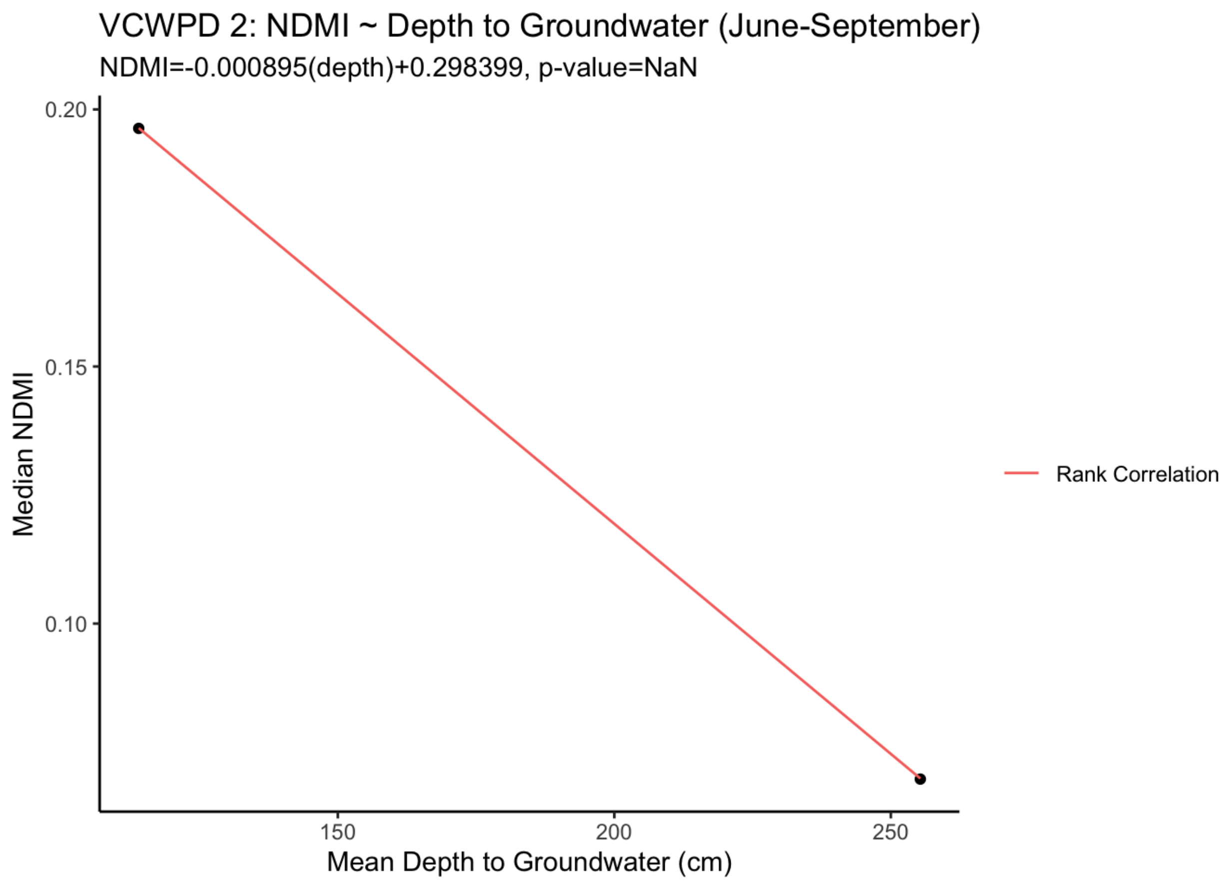
vc2

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc2_summer)
##
## Coefficients:
##                Estimate Std. Error t.value p.value
## (Intercept)  0.66798977        NaN     NaN     NaN
## mean_dtg    -0.00091227        NaN     NaN     NaN
##
## Multiple R-squared (Robust): NaN
## Reduction in Dispersion Test: 0 p-value: NaN
```



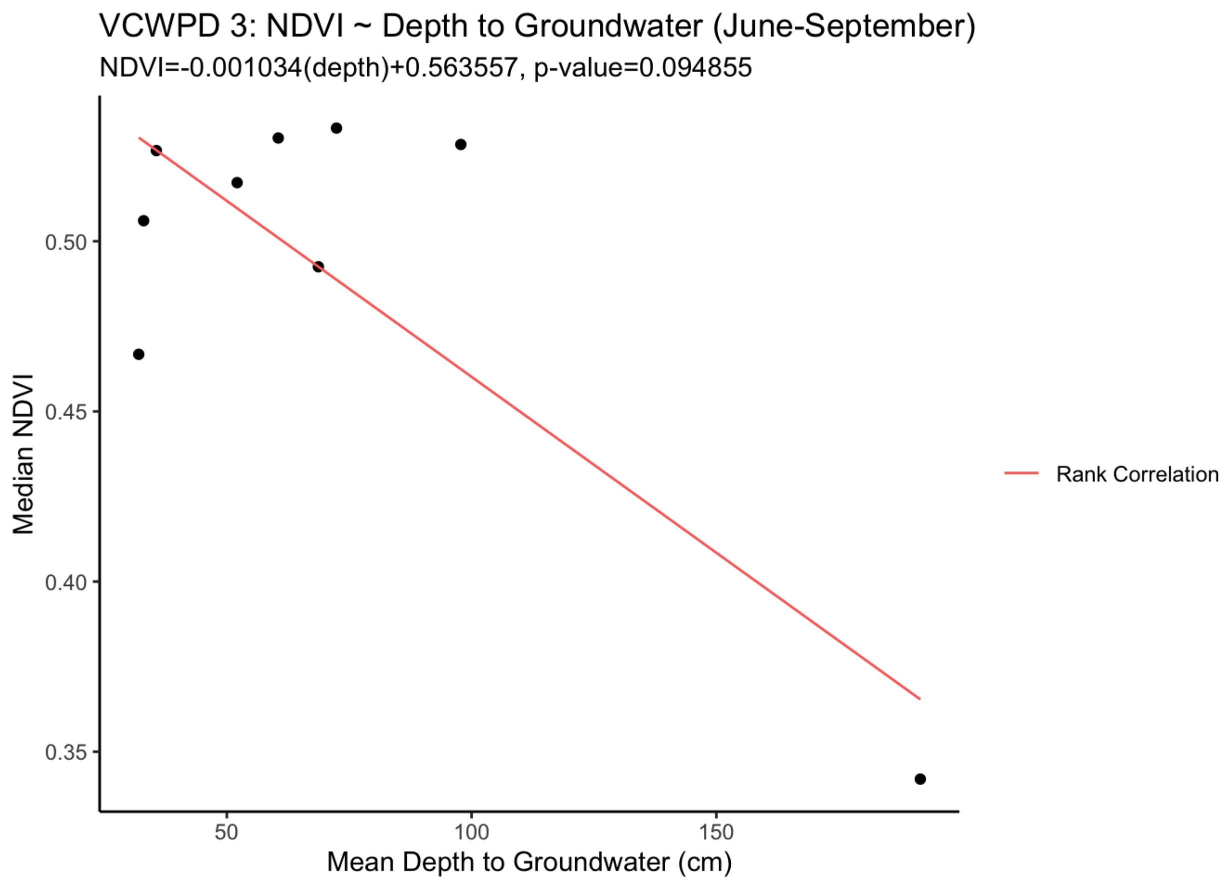
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc2_summer)
##
## Coefficients:
##              Estimate Std. Error t.value p.value
## (Intercept)  0.29839937        NaN     NaN     NaN
## mean_dtg    -0.00089549        NaN     NaN     NaN
##
## Multiple R-squared (Robust): NaN
## Reduction in Dispersion Test: 0 p-value: NaN
```



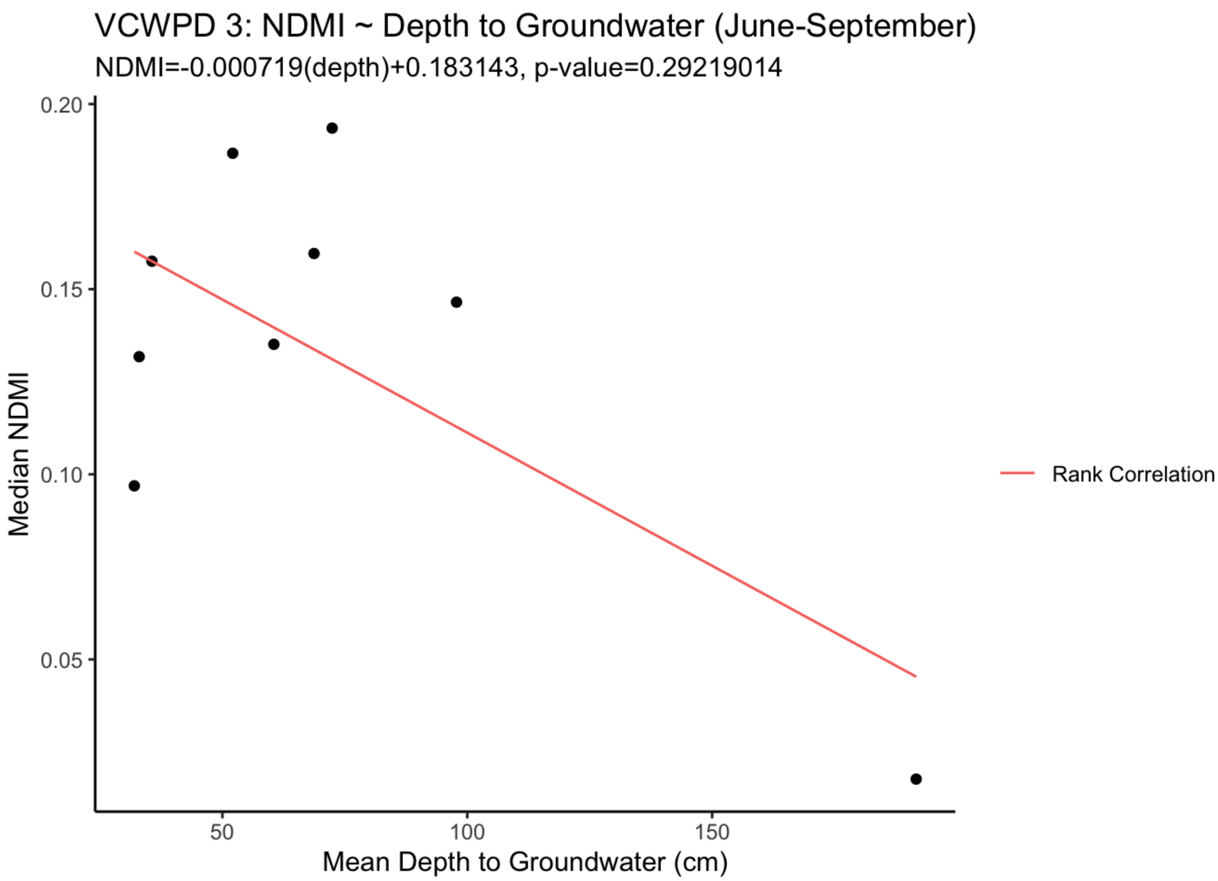
vc3

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc3_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.56355715  0.04380953 12.8638 3.983e-06 ***
## mean_dtg    -0.00103419  0.00053571 -1.9305   0.09486 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.2466697
## Reduction in Dispersion Test: 2.29207 p-value: 0.17381
```



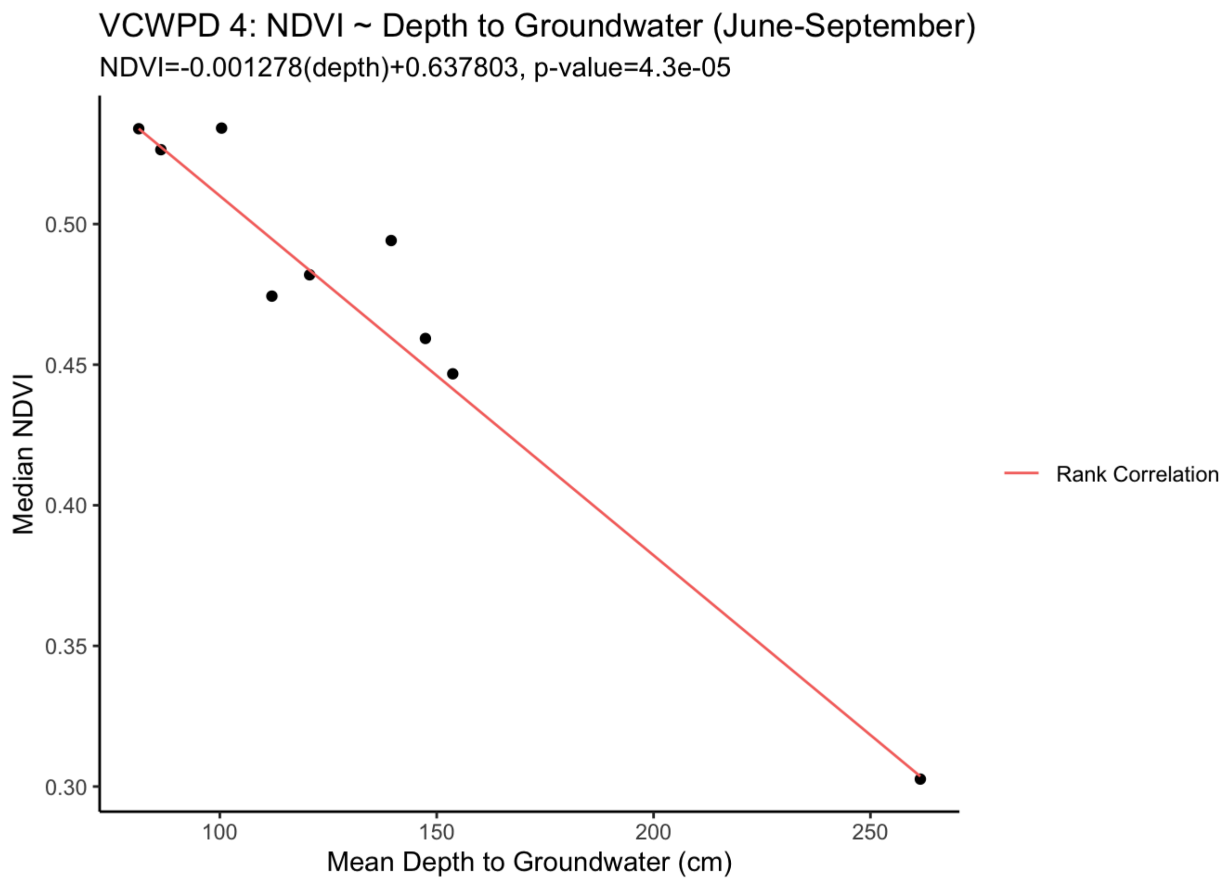
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc3_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value  p.value
## (Intercept)  0.18314334  0.04999297  3.6634 0.008034 **
## mean_dtg    -0.00071899  0.00063127 -1.1390 0.292190
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.1982992
## Reduction in Dispersion Test: 1.73144 p-value: 0.22968
```



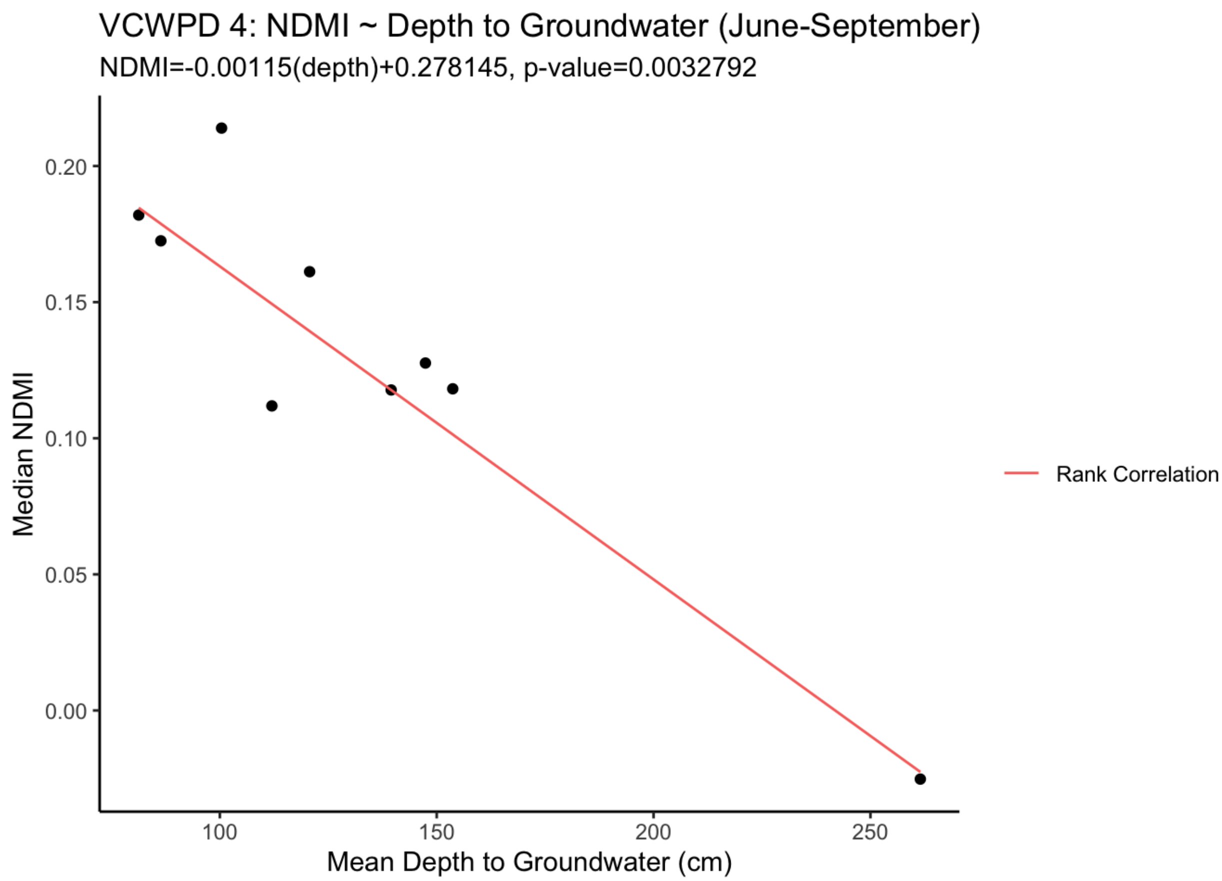
vc4

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc4_summer)
##
## Coefficients:
##              Estimate Std. Error t.value   p.value
## (Intercept)  0.6378032  0.0206969  30.816 9.781e-09 ***
## mean_dtg    -0.0012781  0.0001422  -8.988 4.303e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.8439916
## Reduction in Dispersion Test: 37.86939 p-value: 0.00047
```



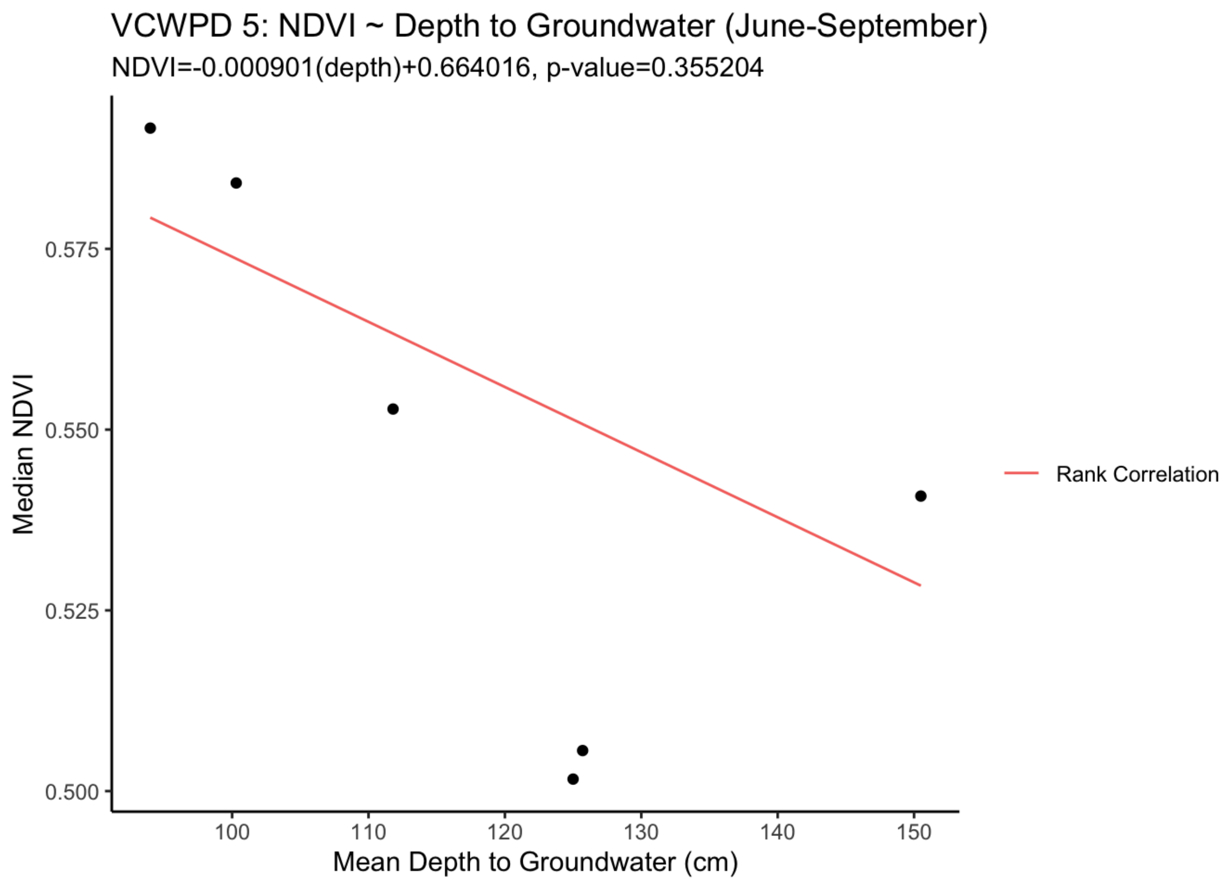
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc4_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.27814501  0.03625878  7.6711 0.0001191 ***
## mean_dtg    -0.00114989  0.00026321 -4.3687 0.0032792 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7018897
## Reduction in Dispersion Test: 16.48124 p-value: 0.00481
```



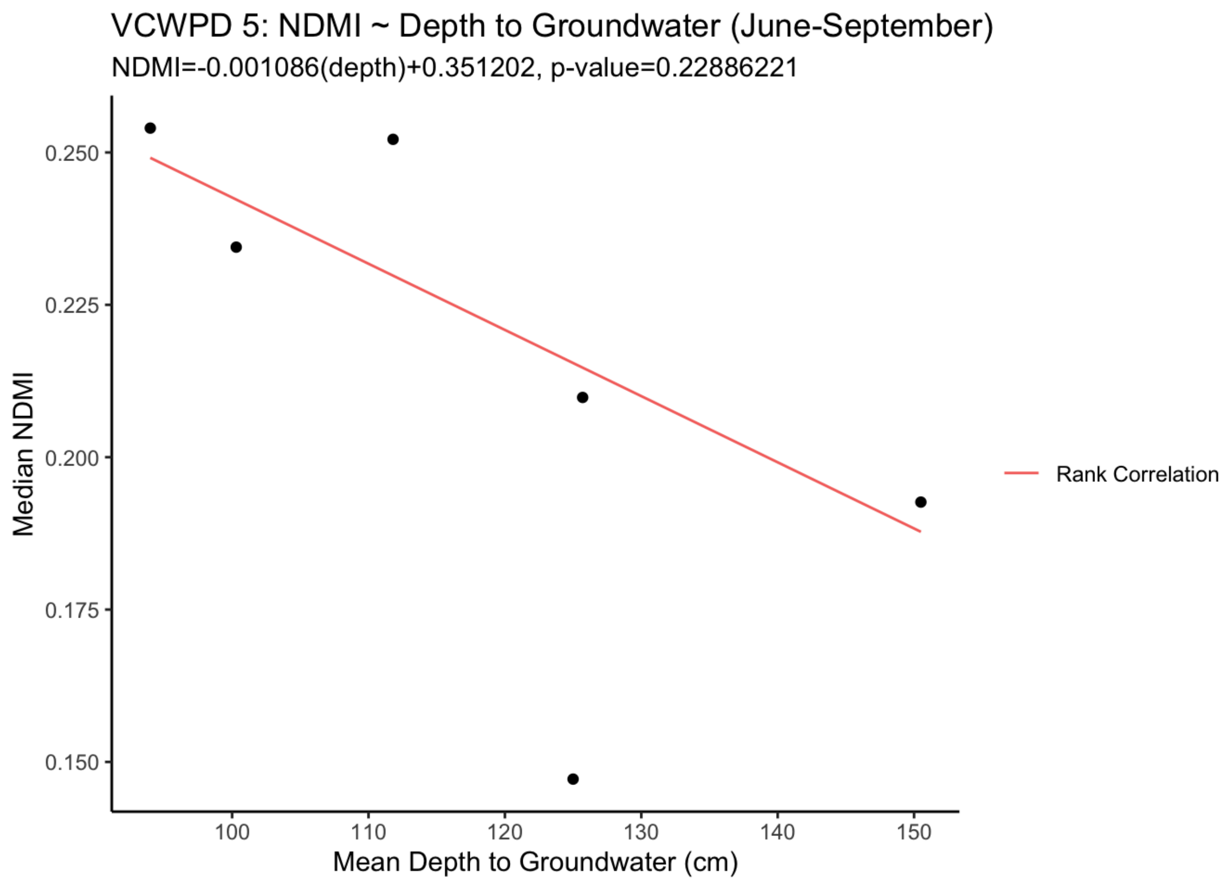
vc5

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc5_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  0.66401585  0.10410675  6.3782  0.0031 **
## mean_dtg    -0.00090084  0.00086243 -1.0445  0.3552
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.437008
## Reduction in Dispersion Test: 3.1049 p-value: 0.15285
```



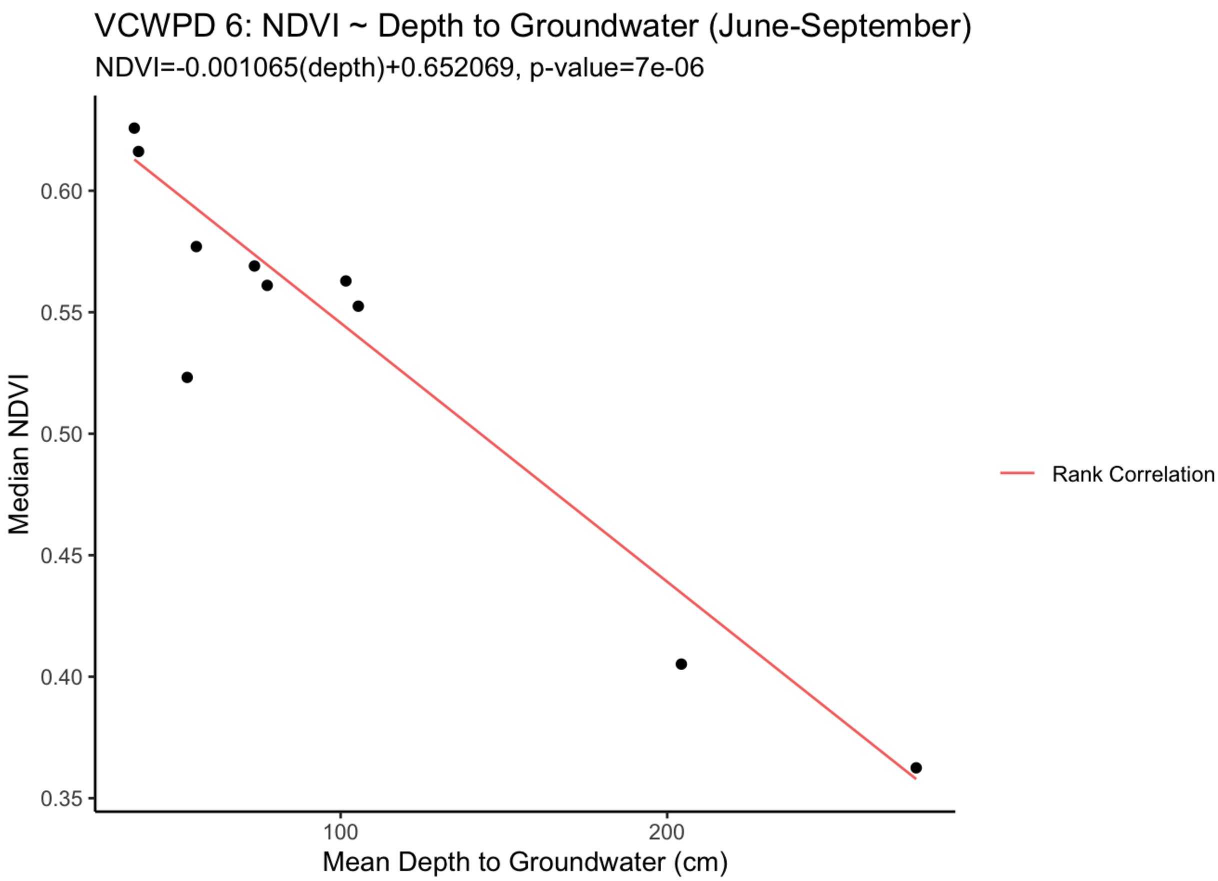
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc5_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value p.value
## (Intercept)  0.35120174  0.09595676  3.6600 0.02158 *
## mean_dtg    -0.00108604  0.00076528 -1.4191 0.22886
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.5162703
## Reduction in Dispersion Test: 4.26908 p-value: 0.1077
```



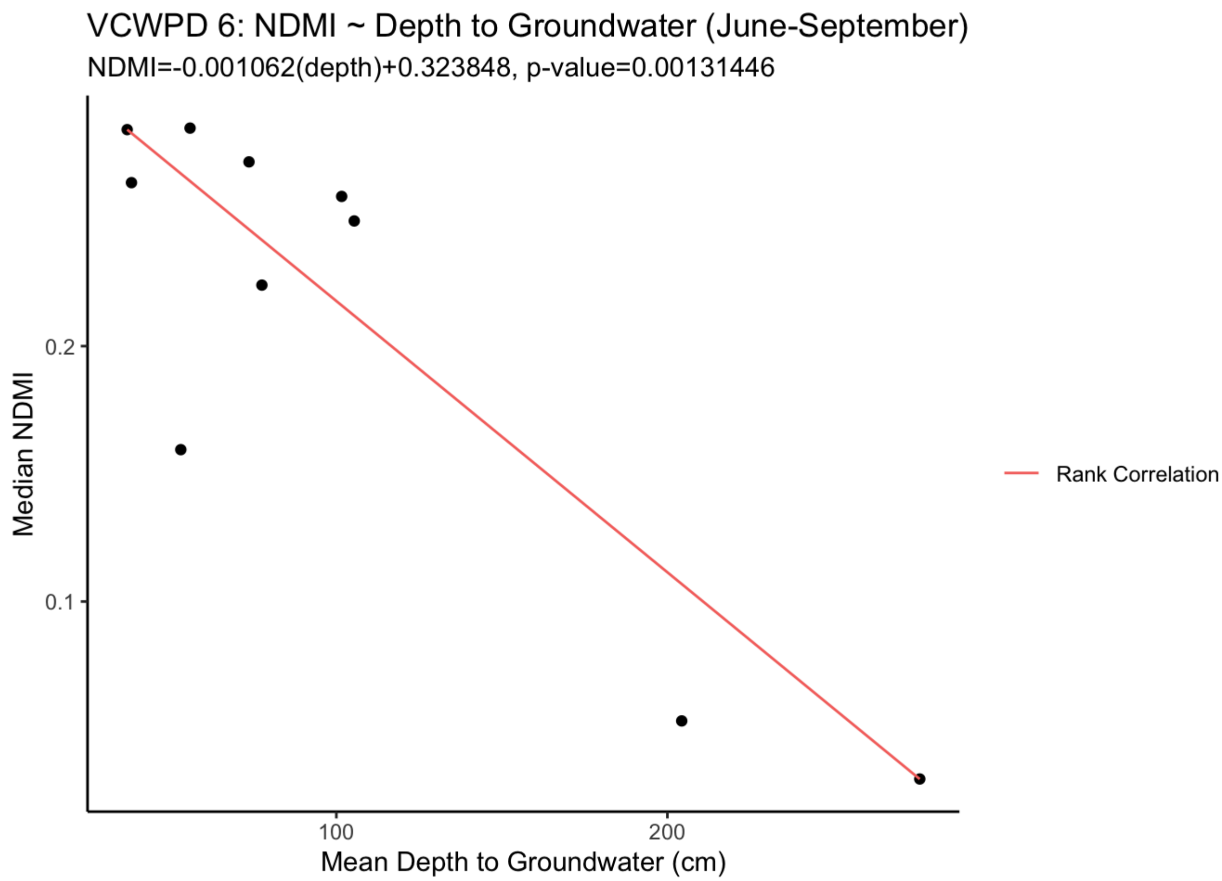
vc6

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc6_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.65206869  0.01670358  39.038 2.038e-10 ***
## mean_dtg    -0.00106507  0.00010435 -10.207 7.285e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.8419074
## Reduction in Dispersion Test: 42.60324 p-value: 0.00018
```



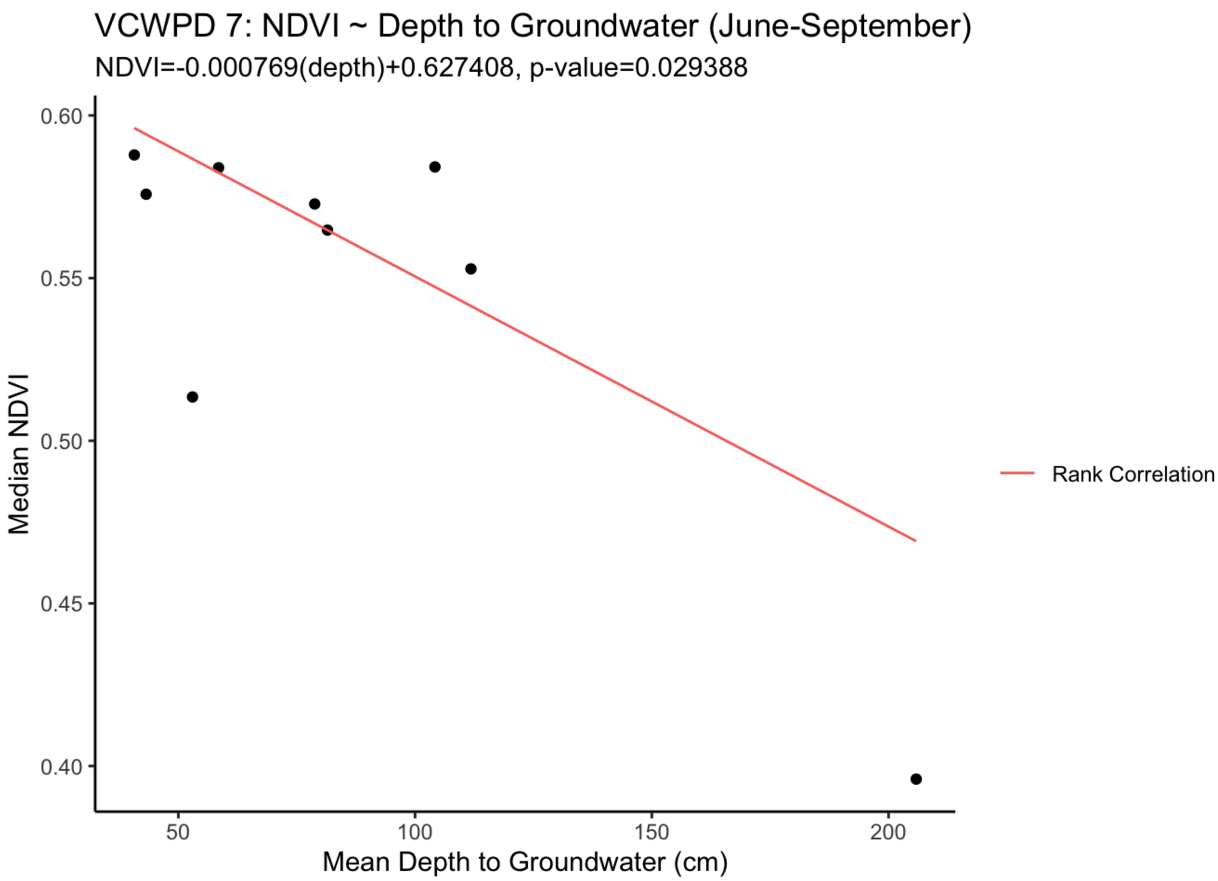
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc6_summer)
##
## Coefficients:
##               Estimate  Std. Error t.value   p.value
## (Intercept)  0.32384805  0.03565618  9.0825 1.733e-05 ***
## mean_dtg    -0.00106185  0.00022011 -4.8241  0.001314 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6673508
## Reduction in Dispersion Test: 16.04936 p-value: 0.00392
```

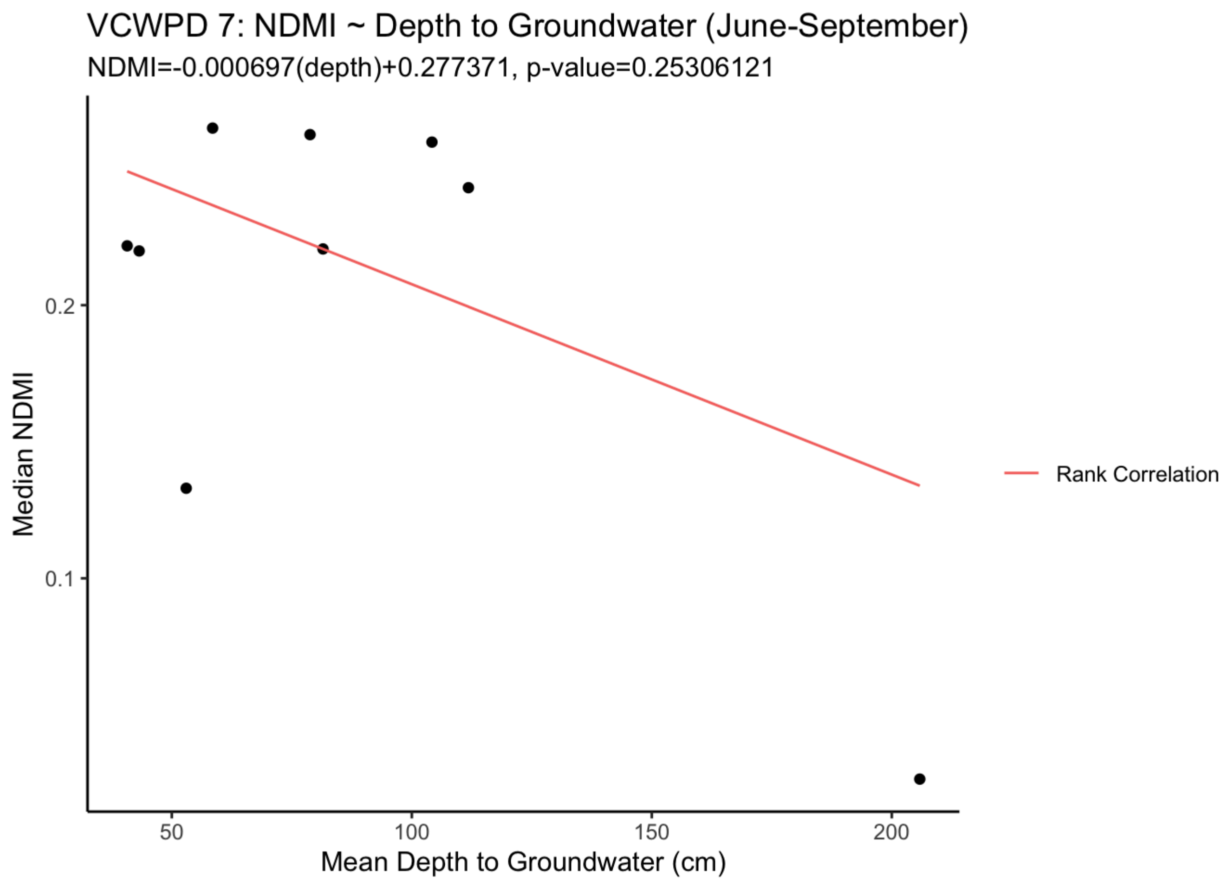


vc7

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc7_summer)
##
## Coefficients:
##                Estimate  Std. Error t.value   p.value
## (Intercept)  0.62740827  0.03592253 17.4656 4.964e-07 ***
## mean_dtg    -0.00076865  0.00028168 -2.7288   0.02939 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.460938
## Reduction in Dispersion Test: 5.98552 p-value: 0.04433
```

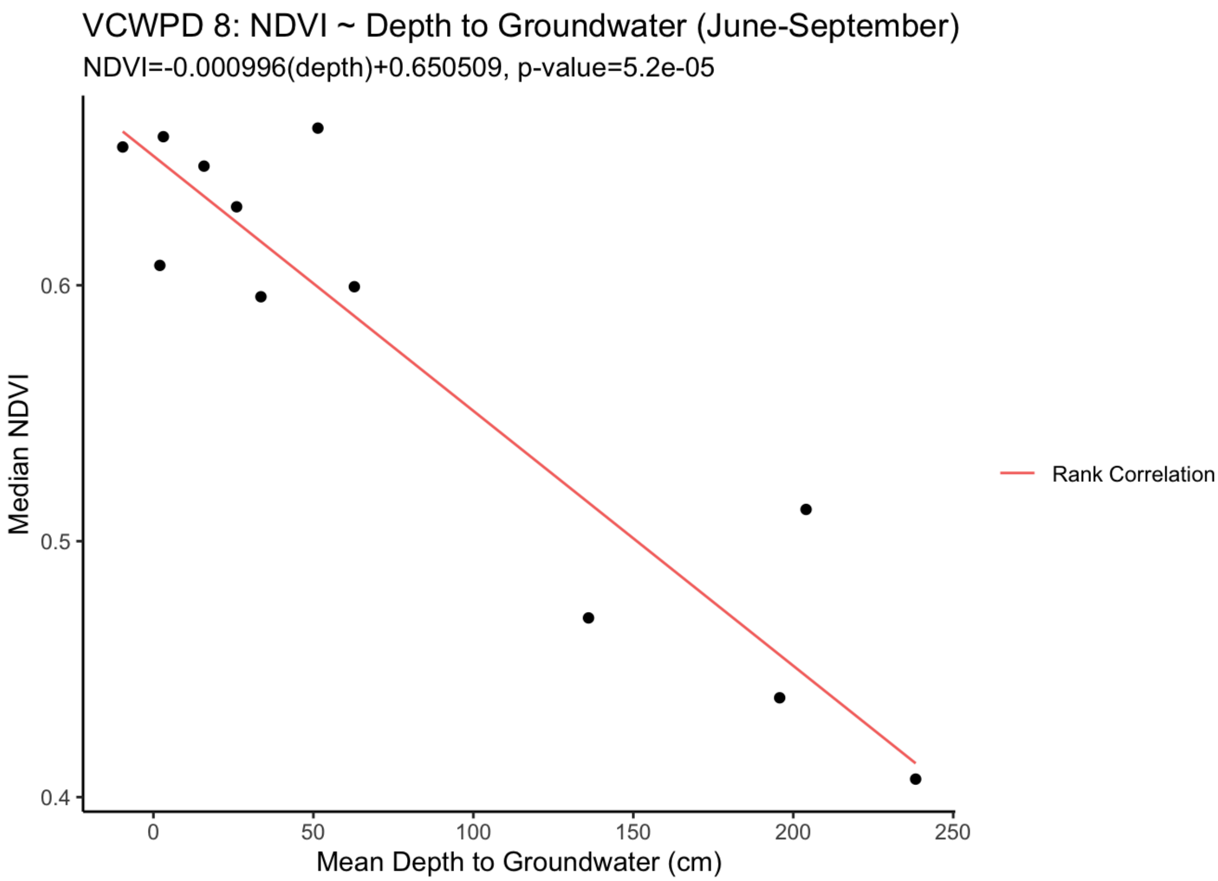



```
Unset
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc7_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value  p.value
## (Intercept)  0.27737132  0.06754232  4.1066 0.004535 **
## mean_dtg    -0.00069672  0.00055945 -1.2454 0.253061
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.1779071
## Reduction in Dispersion Test: 1.51485 p-value: 0.25815
```



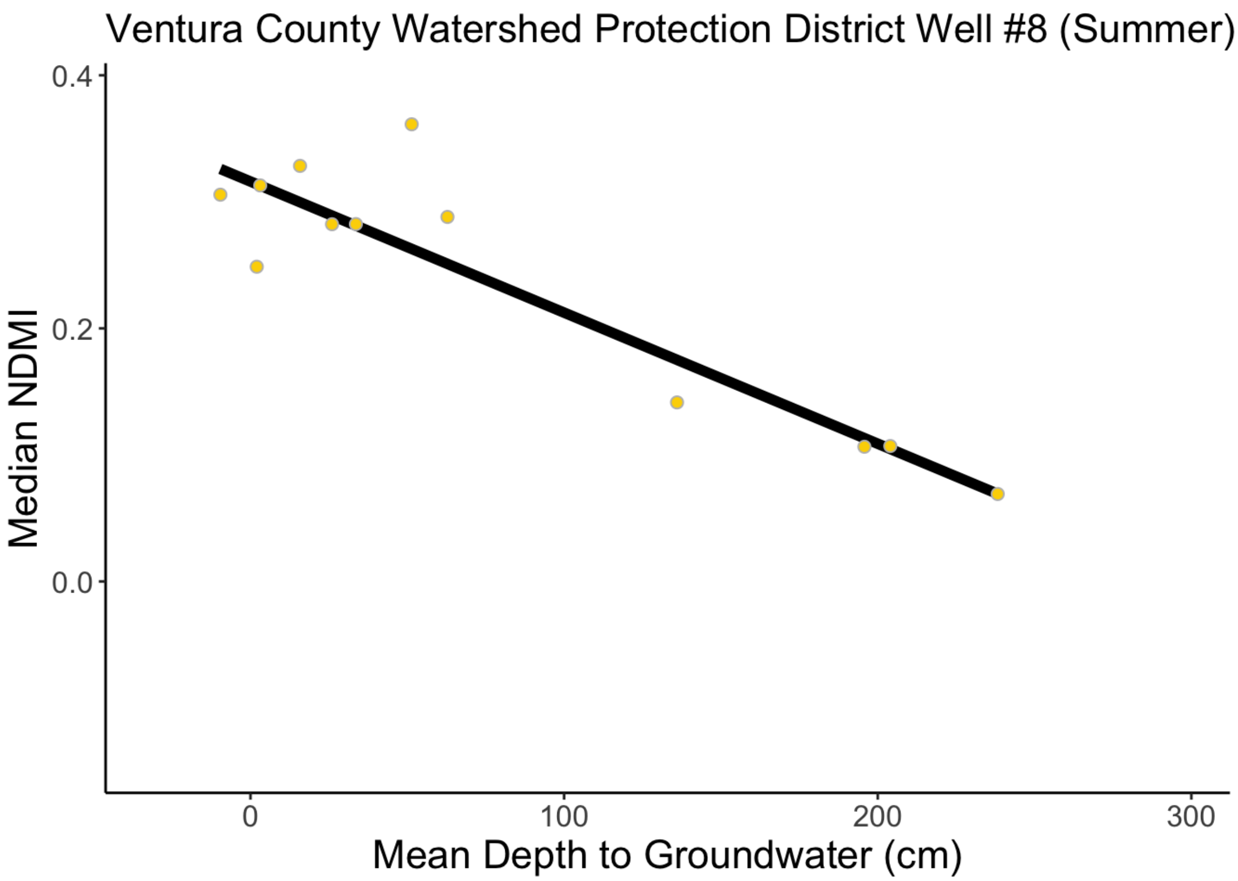
vc8

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc8_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.65050893  0.01536870 42.3269 1.300e-12 ***
## mean_dtg    -0.00099649  0.00014801 -6.7325 5.152e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.746469
## Reduction in Dispersion Test: 29.44291 p-value: 0.00029
```



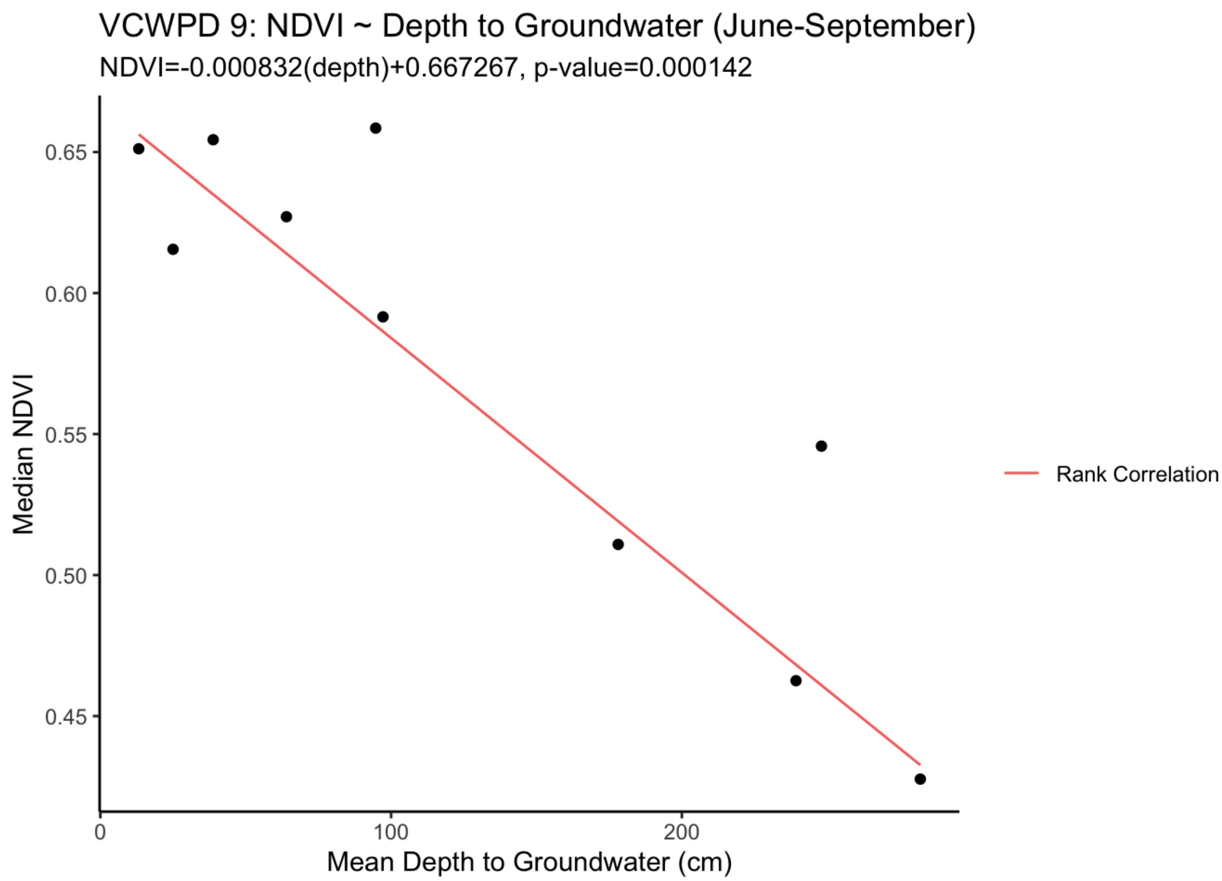
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc8_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.31605423  0.01861712 16.9765 1.059e-08 ***
## mean_dtg    -0.00103589  0.00014676 -7.0585 3.463e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7672719
## Reduction in Dispersion Test: 32.9686 p-value: 0.00019
```



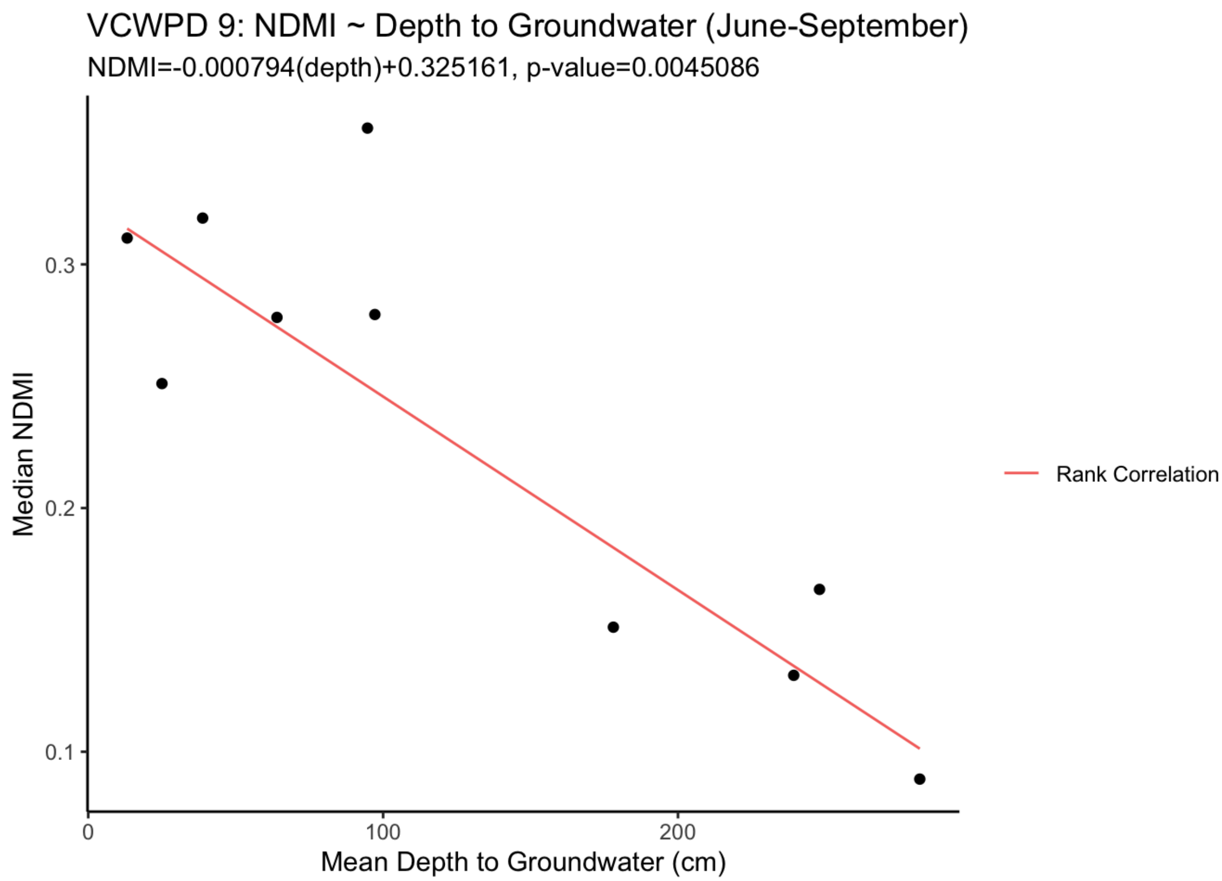
vc9

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc9_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.66726691  0.02858223 23.3455 1.204e-08 ***
## mean_dtg    -0.00083151  0.00012277 -6.7729 0.0001417 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7629999
## Reduction in Dispersion Test: 25.75526 p-value: 0.00096
```



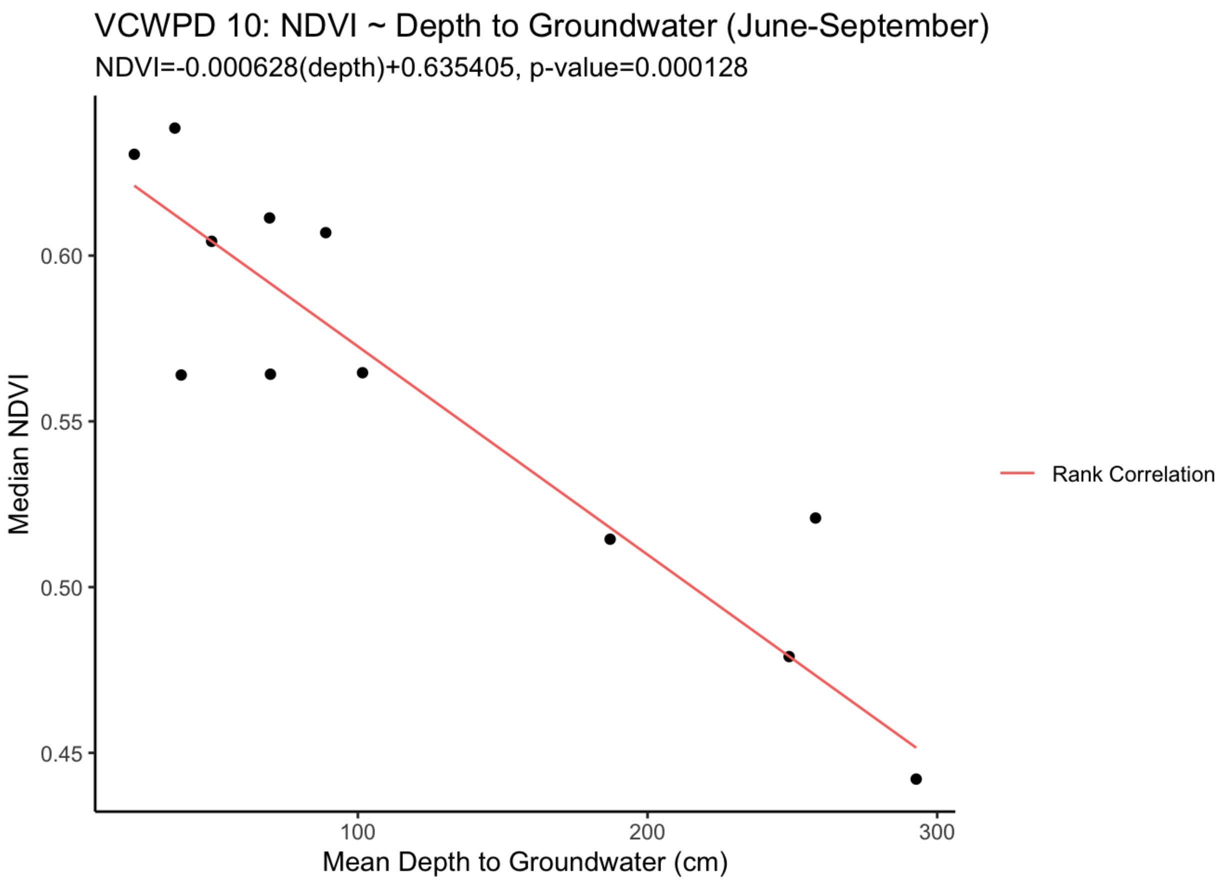
Unset

```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc9_summer)
##
## Coefficients:
##                 Estimate  Std. Error t.value   p.value
## (Intercept)  0.32516060  0.03385083  9.6057 1.145e-05 ***
## mean_dtg    -0.00079383  0.00020325 -3.9056  0.004509 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.6620588
## Reduction in Dispersion Test: 15.67275 p-value: 0.00418
```

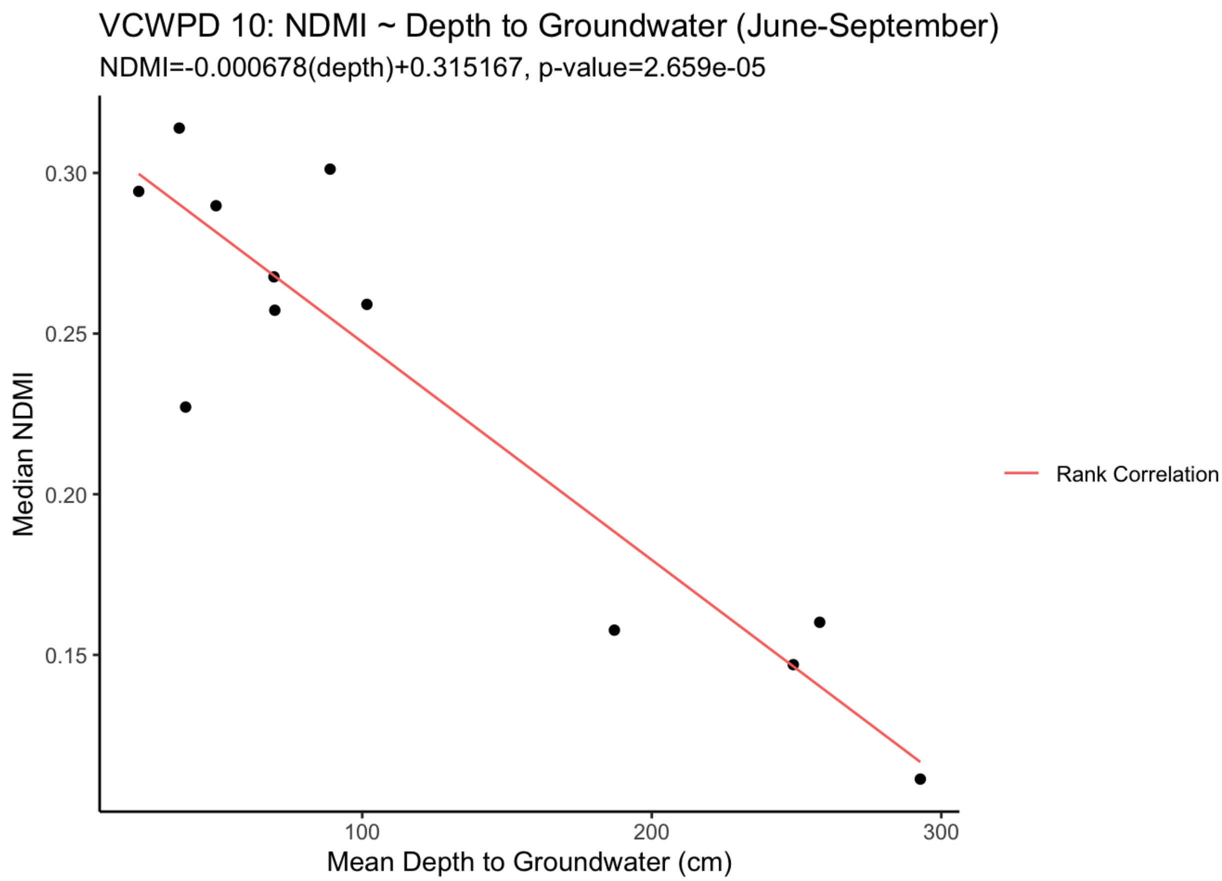


vc10

```
Unset
## Call:
## rfit.default(formula = NDVI_Median ~ mean_dtg, data = rd_vc10_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  0.63540518  0.01648677 38.5403 3.301e-12 ***
## mean_dtg    -0.00062827  0.00010432 -6.0222 0.0001283 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.714992
## Reduction in Dispersion Test: 25.08673 p-value: 0.00053
```



Unset
```
## Call:
## rfit.default(formula = NDMI_Median ~ mean_dtg, data = rd_vc10_summer)
##
## Coefficients:
##              Estimate  Std. Error t.value   p.value
## (Intercept)  3.1517e-01  1.4464e-02 21.7904 9.267e-10 ***
## mean_dtg    -6.7753e-04  9.3052e-05 -7.2812 2.659e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Multiple R-squared (Robust): 0.7692756
## Reduction in Dispersion Test: 33.34175 p-value: 0.00018
```



References

Bell, I., Berry, E., Booth, D., McKelvey, Z., Prentice-Dekker, B., Steele, M. (2016). *Economic Analysis of Invasive Giant Reed (Arundo donax) Control for the Lower Santa Clara River.* (Master's thesis, University of California, Santa Barbara).

Beller, E. E., B. K. Orr, M. N. Salomon, R. M. Grossinger, S. J. Dark, E. D. Stein, T. R. Longcore, G. C. Coffman, A. A. Whipple, R. A. Askevold, B. Stanford, J. R. Beagle, P. W. Downs. (2011). *Historical ecology of the lower Santa Clara River, Ventura River, and Oxnard Plain: an analysis of terrestrial, riverine, and coastal habitats*. Prepared for the State Coastal Conservancy. A report of SFEI's Historical Ecology Program, SFEI Publication #641, San Francisco Estuary Institute, Oakland, CA.

Beller, E. E., P. W. Downs, R. M. Grossinger, B. K. Orr, and M. N. Salomon. (2016). From past patterns to future potential: using historical ecology to inform river restoration on an intermittent California river. Landscape Ecology 31: 581-600. https://link.springer.com/article/10.1007/s10980-015-0264-7

California Department of Water Resources. (2023). *California Irrigation Management Information System.* CA Department of Water Resources CIMIS. https://cimis.water.ca.gov/WSNReportCriteria.aspx

California Department of Water Resources. (2023). *SGMA Data Viewer.* https://sgma.water.ca.gov/webgis/config/custom/html/SGMADataViewer/doc/

California State Water Resources Control Board. (n.d.). *The Sustainable Groundwater Management Act*. California State Water Boards. https://www.waterboards.ca.gov/water_issues/programs/sgma/about_sgma.html

Cordero, J. F. (2015). *Native Persistence: Marriage, Social Structure, Political Leadership, and Intertribal Relations at Mission Dolores, 1777–1800*. Journal of California and Great Basin Anthropology. UC Merced. https://escholarship.org/uc/item/1s8646hp

Court, D., F. Ogushi, J. Glatzer, J. McDonald, K. Keith, S. Hard. (2000). *Prioritizing Sites along the Santa Clara River for Conservation of Threatened and Endangered Species*. (Master's thesis, University of California, Santa Barbara). https://santaclarariver.org/wp-content/uploads/2022/05/SantaClara_final.pdf

Downs, P. W., Dusterhoff, S. R., Sears, W. A. (2013). *Reach-scale channel sensitivity to multiple human activities and natural events: Lower Santa Clara River, California, USA*. Geomorphology 189:121-134. DOI:10.1016/j.geomorph.2013.01.023

Fillmore & Piru Basins Groundwater Sustainability Agency. (n.d.) *Sustainable Groundwater Management Act Overview.* https://www.fpbgsa.org/gsa-formations/sustainable-groundwater-management-act-overview/

Gao, B.C. (1996). *NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space.* Remote Sensing of Environment, 58(3), 257–266

Goldstein-Greenwood, J. (28 April 2023). Theil-Sen Regression: Programming and Understanding an Outlier-Resistant Alternative to Least Squares. University of Virginia Library. University of Virginia. https://library.virginia.edu/data/articles/theil-sen-regression-programming-and-understanding-an-outlier-resistant-alternative-to-least-squares

Higgins, P. (1996). The Tataviam: Early Newhall Residents. Old Town Newhall Gazette. https://scvhistory.com/scvhistory/higgins-tataviam.htm

Johnson, A. I. (1967). *Specific yield: compilation of specific yields for various materials*. Report. Water Supply Paper 1662. US Geological Survey. doi: 10.3133/wsp1662D

Kim, D., Zhang, H., Zhou, H. *et al.* (2015). *Highly sensitive image-derived indices of water-stressed plants using hyperspectral imaging in SWIR and histogram analysis*. Sci Rep **5**, 15919 . https://doi.org/10.1038/srep15919

Kløve, B., Ala-Aho, P., Bertrand, G., Gurdak, J. J., Kupfersberger, H., Kværner, J., Muotka, T., Mykrä, H. Preda, E., Rossi, P., Uvo, C. B., Velasco, E., & Pulido-Velazquez, M. (2014). *Climate change impacts on groundwater and dependent ecosystems*. Journal of Hydrology, 518, 250–266. https://doi.org/10.1016/j.jhydrol.2013.06.037

Levi, S., & Yeats, R. S. (1993). Paleomagnetic constraints on the initiation of uplift on the Santa Susana Fault, Western Transverse Ranges, California. *Tectonics*, *12*(3), 688–702. https://doi.org/10.1029/93TC00133

Minor, A. Scott, Kellog, S. Karl, Stanley, G. Richard, Gurrola, D. Larry, Keller, A. Edward, Brandt, R. Theodore (2009). Geologic Map of the Santa Barbara Coastal Plain Area, Santa Barbara County, California. *USGS, Scientific Investigations Map. https://pubs.usgs.gov/sim/3001/downloads/pdf/SIM3001pamphlet.pdf*

Mound Basin GSA. (n.d.) *Home*. Mound Basin GSA. https://www.moundbasingsa.org/

National Marine Fisheries Service. (2012). *Southern California Steelhead Recovery Plan.* Southwest Region, Protected Resources Division, Long Beach, California.

Oakley, N. S., Hatchett, B. J., McEvoy, D., Rodriguez, L. (2019). *Projected Changes in Ventura County Climate*. Western Regional Climate Center, Desert Research Institute, Reno, Nevada.

Pennsylvania State University. (2023). *T1.1 - Robust Regression Methods*. Stat 501: Regression Methods. The Pennsylvania State University. https://online.stat.psu.edu/stat501/lesson/t/t.1/t.1.1-robust-regression-methods

Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J., Tucker, C.J., Stenseth, N.C. (2005). *Using the satellite-derived NDVI to assess ecological responses to environmental change.*TRENDS in Ecology and Evolution, 20(9), 503–10. doi:10.1016/j.tree.2005.05.011

Practitioners of Nature, Wishtoyo Chumash Village. (8 October 2011). Excerpt from the Declaration of the Gathering of Indigenous Spiritual Leaders. https://www.wishtoyo.org/spiritual-physical-and-community-wellness

PRISM Climate Group. (2023). *Time-Series Values for Individual Locations.* Oregon State University. https://prism.oregonstate.edu/explorer/

Rhew IC, Vander Stoep A, Kearney A, Smith NL, Dunbar MD. (2011). *Validation of the normalized difference vegetation index as a measure of neighborhood greenness*. Ann Epidemiol., 21(12), 946-52. doi: 10.1016/j.annepidem.2011.09.001.

Rohde, M. M., Roberts, D. A., Singer, M. B., Stella, J. C. (2021). *Groundwater dependence of riparian woodlands and the disrupting effect of anthropogenically altered streamflow*. Proc National Academy of Sciences 118:e2026453118.

Rotzien, J., Lowe, D., & Schwalbach, J. (2014). *Processes of Sedimentation and Stratigraphic Architecture of Deep-Water Braided Lobe Complexes*: The Pliocene Repetto and Pico Formations, Ventura Basin, U.S.A. *Journal of Sedimentary Research*, *84*, 910–934. https://doi.org/10.2110/jsr.2014.71

Santa Barbara Museum of Natural History. (2023). *Sukinanik'oy Garden of Chumash Plants*. SBMNH. https://www.sbnature.org/visit/exhibitions/87/sukinanikoy-garden-of-chumash-plants

Soil Survey Staff. (2023). *Gridded Soil Survey Geographic (gSSURGO) Database for California*. United States Department of Agriculture. Natural Resources Conservation Service. Available online at https://gdg.sc.egov.usda.gov/. *November 18, 2023* (FY23 official release).

Stillwater Sciences. (2011). *Geomorphic assessment of the Santa Clara River watershed: synthesis of the lower and upper watershed studies, Ventura and Los Angeles counties, California*. Prepared by Stillwater Sciences, Berkeley, California for Ventura County Watershed Protection District, Los Angeles County Department of Public Works, and the U.S. Army Corps of Engineers–L.A. District.

Stillwater Sciences. (2021). *Assessment of Groundwater Dependent Ecosystems for the Fillmore and Piru Basins Groundwater Stability Plan*. Tech Memo. for Fillmore and Piru Basins Groundwater Sustainability Agency, Fillmore. https://s29420.pcdn.co/wp-content/uploads/2022/02/Appendix-D_GDE-Tech-Memo-1.pdf

Stillwater Sciences. (n.d.) *Southern steelhead — Santa Clara River Parkway*. https://parkway.scrwatershed.org/theriver/species/southern-steelhead.html

Strashok, O., Ziemiańska, M., Strashok, V. (2022). *Evaluation and Correlation of Normalized Vegetation Index and Moisture Index in Kyiv (2017–2021)*. Journal of Ecological Engineering, 23(9), 212-218. https://doi.org/10.12911/22998993/151884

The Nature Conservancy. (January 2018). *Groundwater Dependent Ecosystems under the Sustainable Groundwater Management Act: Guidance for Preparing Groundwater*

Sustainability Plans. The Nature Conservancy. https://www.scienceforconservation.org/assets/downloads/GDEsUnderSGMA.pdf

The Nature Conservancy. (2023). *What are Groundwater Dependent Ecosystems and why are they important?* The Nature Conservancy. https://groundwaterresourcehub.org/

United States Fish and Wildlife Service. (1973). *Endangered Species Act of 1973: As Amended through the 108th Congress.* Department of the Interior. https://www.fws.gov/sites/default/files/documents/endangered-species-act-accessible_7.pdf

United States Fish and Wildlife Service. (16 December 1994) *Determination of Endangered Status for the Arroyo Southwestern Toad*. Department of the Interior. https://www.fws.gov/species-publication-action/etwp-determination-endangered-status-arroyo-southwestern-toad

United States Fish and Wildlife Service. (23 May 1996) *Determination of Threatened Status for the California Red-legged Frog*. Department of the Interior. https://www.fws.gov/species-publication-action/etwp-determination-threatened-status-california-red-legged-frog

United States Fish and Wildlife Service. (22 March 2018). *Unarmored Three-Spine Stickleback.* Environmental Conservation Online System. https://ecos.fws.gov/ecp/species/7002#status

United States Geological Survey. (3 January 2017). *Water-Table Fluctuation (WTF) Method*. Groundwater Resources Program. US Geological Survey. https://water.usgs.gov/ogw/gwrp/methods/wtf/

United States Geological Survey. (3 January 2017). *Water-Table Fluctuation (WTF) Method: Key Assumptions and Critical Issues*. Groundwater Resources Program. US Geological Survey. https://water.usgs.gov/ogw/gwrp/methods/wtf/issues_limititations.html

Utom Conservation Fund. (n.d.) *The Utom River Watershed: Southern California's Signature River.* Utom Conservation Fund. https://utomriverconservation.org/the-utom-river-watershed/

Wishtoyo Chumash Foundation. (2022). *About Us.* Wishtoyo Chumash Foundation. https://www.wishtoyo.org/about-us

Wishtoyo Chumash Foundation. (2022). *Chumash History.* Wishtoyo Chumash Foundation. https://www.wishtoyo.org/cp-chumash-history

Wishtoyo Chumash Foundation. (2022). *Santa Clara River Estuary Restoration.* Wishtoyo Chumash Foundation. https://www.wishtoyo.org/santa-clara-river-estuary-restoration

Wolf, J. (15 August 2017). *Revealing the history of genocide against California's Native Americans*. Newsroom. UCLA. https://newsroom.ucla.edu/stories/revealing-the-history-of-genocide-against-californias-native-americans