Memorandum

Topic:	***Executive Summary of CRSWUA Groundwater Investigation***
Project:	***Technical Support for Enhancing the Understanding of the Groundwater System***
Date:	***September 30, 2021***
By:	***Enrique Triana, Ryan Johnson, and Ben Lord***

Overview of Study

The goal of this study, performed by RTI International, was to use the new Conejos River System Water Users Association (CRSWUA) confined aquifer monitoring network data to enhance the understanding of the groundwater system in the San Luis Valley and particularly the confined aquifer behavior in the sub-district area associated with the CRSWUA. The CRSWUA installed confined aquifer monitoring transducers in existing wells throughout the area of interest that collect aquifer measurements multiple times a day. Figure 1 shows the locations of all considered sites for CRSWUA wells during the project.

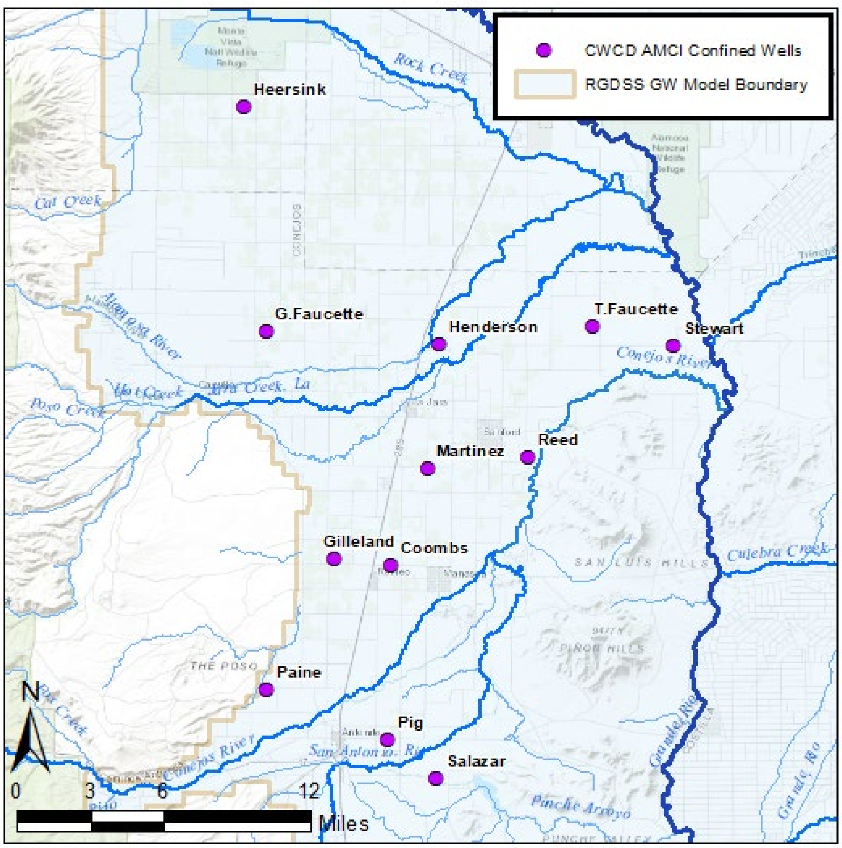

Figure 1. Locations of CRSWUA wells.

RTI developed a data management system in order to download and quality control these groundwater monitoring data as well as other hydrologic data (precipitation, snow, streamflow, etc.) and groundwater monitoring data from other sources (USGS) in the area. The study can be summarized by the following three analyses:

1. Temporal/Spatial Aquifer Trends Based on CRSWUA Data
2. Correlation/Comparison of CRSWUA Data to USGS Data
3. Impact of other Hydrologic Factors
4. Development of Groundwater Predictive Model

The following sections present conclusions from each of these analyses.

Temporal/Spatial Aquifer Trends Based on CRSWUA Data

To analyze the temporal and spatial aquifer trends shown by CRSWUA data RTI used single linear regression relationships, multiple regression relationships, time lagged correlations and spatial elevation plots only using these data. In contrast to USGS groundwater monitoring wells with low temporal resolution, the high-resolution CRSWUA well data allowed for a more comprehensive view into aquifer behavior across different locations at different times of the season. This analysis allowed for the development of the following observations and conclusions:

1. <u>Annual Delta of CRSWUA Wells are Correlated:</u>

   When looking at the overall recharge (peak of one year to the peak of following year) all wells showed similar responses. The magnitude or timing of the recharge may be different due to factors such as well depth or proximity to confined pumping wells or proximity to the edge of the aquifer, but from year to year the wells typically either shows a uniform positive or negative response, i.e., all the sites follow the same pattern.

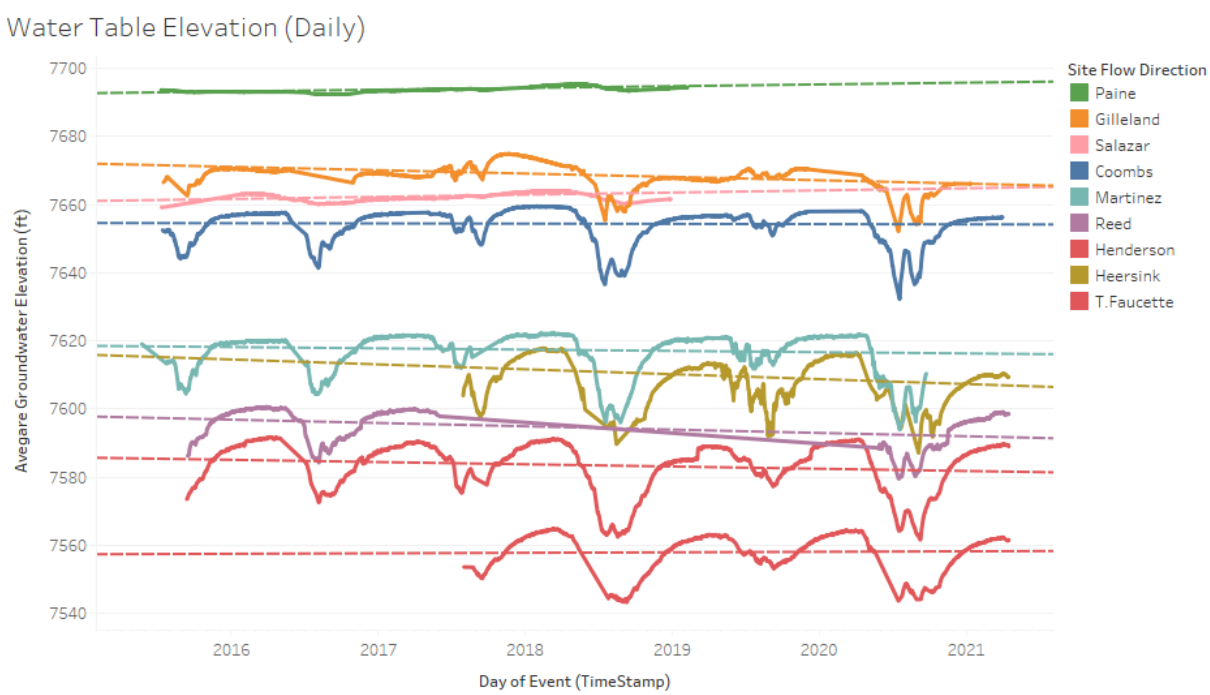

Figure 2. Summary of all available groundwater elevation data from CRSWUA wells.

2. <u>CRSWUA Wells Show Similar Recharge Patterns:</u>

Most wells showed the same recharge pattern that typically starts in early September and slowly approaches the highest recovery point in March and early April. In some cases, for example the Gilleland well, the aquifer response seems different than at other locations nearby that are consistent with the recharge trends in most wells. It is possible that other factors are affecting those measurements and therefore, it is recommended to focus analyses on site with measurements that are consistent with USGS confined aquifer wells and majority of CRSWUA confined aquifer wells.

3. <u>Higher Elevation Wells Show Less Seasonal Fluctuation:</u>

   The water table elevation increases as you move further west away from the Rio Grande River. Wells furthest to the southwest (Paine, Salazar) therefore had the highest elevations. These higher elevation stations showed smaller magnitudes of seasonal drawdown during the pumping season. This is likely due to the decreased density of confined aquifer pumps near these wells.

4. <u>Pressure Waves and Recharge Move Toward the River:</u>

   The groundwater elevations calculated with the groundwater depth and the ground elevation at the monitoring network reveals potential directions of the groundwater flow, from areas of higher elevation (pressure) to lower elevation. Time lagged correlation analyses showed that the recharge of groundwater in stations with typical annual fluctuation (excluding higher elevation wells and Gilleland) typically moves in underground waves from southwest to northeast toward the Rio Grande and in the direction of decreasing water table elevation. Figure 2 shows an example of the inferred flow directions from spatially interpolated groundwater elevation and estimated travel times based on time lagged correlation analyses.

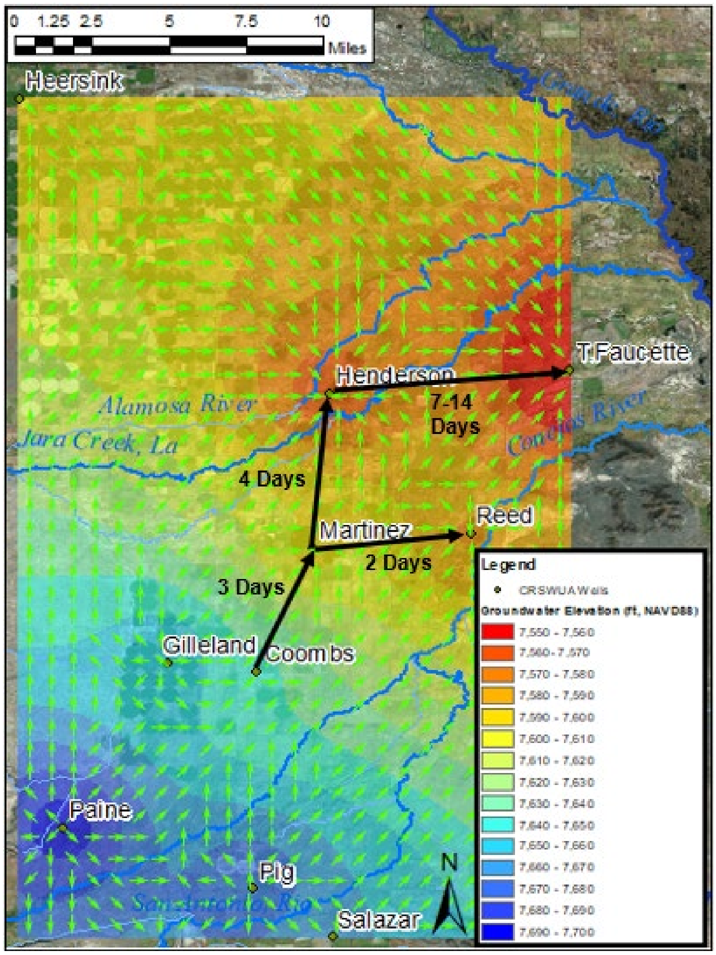

Figure 3. Direction of groundwater flow and estimated travel times between CRSWUA wells.

Correlation/Comparison of CRSWUA Data to USGS Data

USGS confined wells provided a reference for historical confined aquifer groundwater levels. With such a short period of observation available for the CRSWUA wells, the USGS wells allowed RTI to look at aquifer behavior over the past few decades and understand if the behavior captured in the USGS measurements represent the behavior observed in the detailed dataset in the sub-district. Also, with the USGS wells installed as monitoring wells only, without screens at different depths, they provide in the overlapping period a base for the confined aquifer behavior to evaluate the degree to which each CRSWUA well is predominantly measuring the confined aquifer response.

1. <u>USGS Confined Wells are Correlated to CRSWUA Wells</u>
   To ensure that the behavior shown in USGS wells showed similarities with the CRSWUA confined aquifer wells in the sub-district, single and multiple regression analyses were completed on the USGS CON01 and CON02 wells and Coombs and Henderson CRSWUA wells. These two sets of wells represented the most consistent and representative wells from each dataset. Results corroborate that the CON1 and CON2 are capturing similar responses of the confined aquifer as registered in Coombs and Henderson wells. Results of a multiple regression analysis showed a

strong signal for predictability of the historical conditions at those two sites based on CON01 and CON02 long-term measurements.

2. Unconfined Aquifer Behaves Independently to Confined Aquifer

   In addition to USGS confined aquifer wells RTI also downloaded and analyzed groundwater elevation data from shallow unconfined aquifer wells in the study area. It was clear from looking at unconfined aquifer levels and nearby streamflow gages that the unconfined aquifer fluctuates daily and seasonally with the amount of streamflow while the confined aquifer behaves differently. This observation also confirms that the measurements at the CRSWUA wells capture the confined aquifer conditions regardless of the multiple well screens.

Impact of other Hydrologic Factors

One of the main questions surrounding aquifer management is how sensitive the aquifer is to changes in hydrologic and human forcings. To answer this question, RTI analyzed snow water equivalent data, precipitation data, streamflow data, reservoir storage data and confined well pumping data from throughout the valley. From that analysis came the following conclusions:

1. Volume of Pumping is Driven by Hydrologic Factors

   As expected, volume of pumping increased during dry years (below average snow water equivalent (SWE) and precipitation) and decreased during wet years. Volume of pumping for a given area of the valley also depends on the availability of other water sources such as reservoir storage.

2. Dry Years Cause Aquifer Drawdown and Wet Years Cause Aquifer Recharge

   When comparing CON01 and CON02 long-term groundwater data to the combined water availability, i.e., peak SWE from the previous year and precipitation during the irrigation season, groundwater recharge from year to year seems to be driven by the calculated water availability.

Development of Groundwater Predictive Model

The ultimate goal of better understanding aquifer behavior aims to build tools supporting management and decision making. The prior analysis was extended further through development of a predictive modeling tool leveraging the highly extensive observations compiled in the DMS to predict future groundwater levels. This tool was developed as a prototype using the R statistical programming language to deploy machine learning (ML) algorithms on a monthly timestep to predict groundwater levels at the start of the next irrigation season (April). Guided by findings in the analysis of aquifer recharge characteristics, the initial application was specifically developed to predict groundwater levels in the USGS wells with long periods of record (CON01 and CON02) using historic meteorological observations as inputs.

Performance of the tool was highly dependent on selection of input data and calculation of secondary time series (such as moving averages and running sums). Overall, the tool was able to achieve consistent satisfactory predictions on independent validation datasets and outperformed linear regressions. The large volume of available data under the DMS and flexibility of ML algorithms to adapt with different inputs warrants further investigation into alternate applications of the tool. These further applications could include integrating NRCS water supply forecasts to improve predictions and exploring relationships between wells to better understand aquifer dynamics.

Over time, as more data is collected and stored in the DMS, the tool will increase in predictive ability and quality. We recommend continuing the data collection under the DMS and exploring improvements to the tool to more closely support the aquifer management.

Conclusions for Supporting Sustainable Aquifer Management

Ground water elevation data from USGS wells across the San Luis Valley have shown a decreasing trend in confined aquifer levels since the 1980's. The magnitude of fluctuation in a given year may be different per well but the overall positive or negative trend across the valley over the course of multiple years is consistent. This dataset shows that the confined aquifer responds to forcings as a single underground reservoir. Up until recently the USGS well data were the only consistent dataset available for monitoring the confined aquifer. The wells installed by CRSWUA contain data with a much higher temporal resolution and allow for a more in depth look into seasonal behaviors such as recharge timing and recharge patterns at different locations in the confined aquifer. As with the USGS data, the RTI analysis of these CRSWUA data confirmed that although different areas may have different seasonal trends, the overall fluctuation from year to year across the aquifer is consistent. Since the confined aquifer behaves as a single underground reservoir, aquifer management should therefore be geared toward a whole aquifer approach in which all areas across the aquifer are managed uniformly.

To sustainably manage the confined aquifer, we need to understand its response to stresses and external conditions. Our ability to actively manage the aquifer and avoid unrecoverable conditions can be supported by tools that help us understand responses. For example, the analysis performed in this project revealed that the depletion or accretion of the confined aquifer is dependent on the availability of water from precipitation, SWE, and reservoir storage. The amount of confined aquifer pumping is the main factor influencing the ability of the confined aquifer to recharge, but the confined aquifer pumping is only a by-product of the amount of water available from other hydrologic sources. Therefore, the future state of the confined aquifer might be predicted based on the current state of the confined aquifer and data from hydrologic sources.

To test this hypothesis RTI created a predictive groundwater model based on USGS well data. The initial application was developed using USGS data to capitalize on the relatively long period of record, allowing more data to be used. This model used machine learning algorithms to predict future groundwater levels from USGS well data and hydrometeorological data. The goal of this predictive model was to predict the change in groundwater levels at a given well from the current time to the start of the next irrigation season (April) when the peak level is anticipated. The predictive model showed promise with calibration R-squared values of 0.73 and validation R-squared of 0.76, outperforming similar analyses conducted with linear regression (R-squared of 0.58). However, this is an initial framework application that warrants further investigation. These types of models are generally enhanced when fed more data and are only as good as the quality of input data. In the future, the CRSWUA data will be invaluable to enhancing the predictive model. Due to their higher temporal resolution, CRSWUA well data provide a higher confidence and level of data quality.

In addition to the finer temporal resolution the CRSWUA well data also help to provide a new spatial footprint for the groundwater monitoring data in the sub-district. Although confined USGS wells are present throughout the valley they are relatively sparse in the area between the Alamosa River and Conejos River. CRSWUA wells also include sites like Salazar and Gilleland near the edge of the aquifer, an area not well represented by USGS wells. This additional spatial coverage allows for a more complete spatial understanding of the confined aquifer for not only the possibility of a more thorough predictive model, but also a way to cross-check the Colorado RGDSS groundwater model.

Recommendations

- Continue the confined aquifer monitoring program.
- Explore with stakeholders practical management tools that can be developed based on this dataset to inform decisions.
- Test and further develop the groundwater recharge predictive tool to explore its implementation for the sub-district aquifer management.
- Work with the current data processing company to create API to make the bulk data accessible. This will allow using the DMS on a regular basis to update the database and enhance the regular identification of issues with the equipment and missing data.
- When there is an overlapping period between the data and the RGDSS groundwater model, look at consistencies with the measured points and look for opportunities to improve the represent the confined aquifer modeling.

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Topic:	***Pilot Aquifer Recharge Predictive Tool for Aquifer Management***
Project:	***Technical Support for Enhancing the Understanding of the Groundwater System***
Date:	***September 21,2021***
By:	***Enrique Triana, Ryan Johnson, and Ben Lord***

Introduction

The goal of this study, performed by RTI International, was to use the new Conejos River System Water Users Association (CRSWUA) confined aquifer data to enhance the understanding of the groundwater system in the San Luis Valley and particularly the confined aquifer behavior in the sub-district area associated with the CRSWUA. To support these efforts, RTI developed a data management system (DMS) to compile, organize, categorize, and quality control the newly CRSWUA collected data as well as other available hydrologic data into one central database (see “Task 3 Technical Memorandum”, July 9, 2019). Spatial and temporal analysis of the data was also performed in this study to help understanding the aquifer response to stresses.

Summary of Findings

The better understanding of the aquifer is required to help managing the aquifer to the specified sustainable operation. The analysis was extended further through development of an aquifer response predictive tool. The primary goal of the tool is to leverage the highly extensive and intensive observations compiled in the DMS database to support decision-making on measures to manage the aquifer. This tool was developed as a prototype using the R statistical programming language to apply machine learning (ML) algorithms on a monthly timestep to predict groundwater levels at the start of the next irrigation season (April).

Performance of the tool was highly dependent on selection of input data and calculation of secondary time series (such as moving averages and running sums). Overall, the tool was able to achieve consistent satisfactory predictions on independent validation datasets. The large volume of available data under the DMS and flexibility of ML algorithms to adapt with different inputs warrants further investigation into alternate applications of the tool. In these data-driven approaches, over time, as more data is collected and stored in the DMS, the tool will increase in predictive ability and quality. We recommend continuing the data collection under the DMS and exploring improvements to the tool to more closely support decision-making in the subdistrict.

Methods

The predictive tool utilizes machine learning, a class of algorithms designed to “learn” and improve their predictive capability independently without explicit guidance from users. Machine learning provides a set of tools for exploring relationships and identifying patterns in very large datasets. The generalized process for developing the tool using ML follows four general steps:

1. Input data assimilation and processing
2. Develop linear regression model
3. Train ML models
4. Select and validate best-performing ML model

Step 1. Input Data Assimilation and processing

As the first step, the tool pulls aggregated daily observations of precipitation, snow water equivalent (SWE), reservoir storage, and groundwater levels from the DMS. Periods of record are compared for each time series (Figure 1).

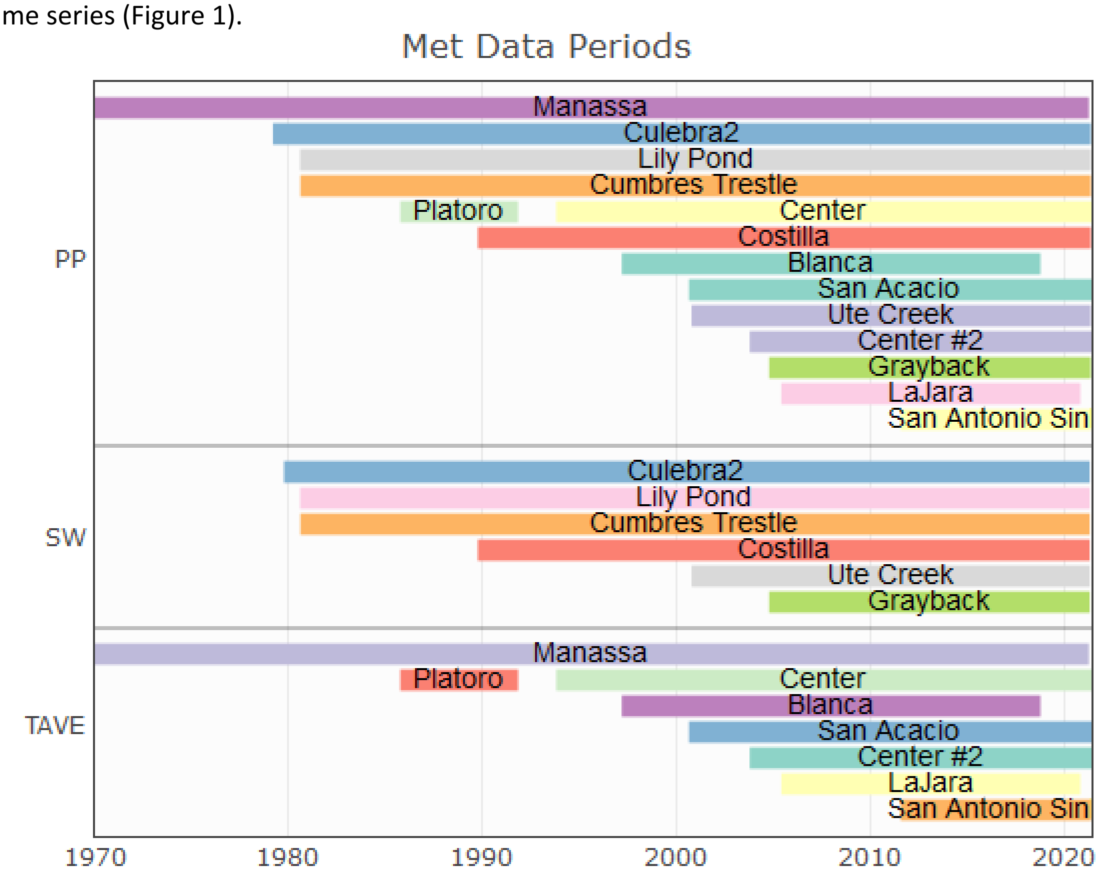

Figure 1. Periods of record for precipitation, temperature, and snow-water

Datasets with long, overlapping periods were selected for this initial tool development. These datasets were then loaded to the tool and further processed to create additional data for training the model at a monthly timestep. Precipitation and SWE datasets were expanded by calculating moving averages and lags for various periods. For example, rainfall data for the month of July, 2009 at a single station would not only include the sum of rainfall during that month, but also a 9-month moving average (the mean of all rainfall from November, 2008 to the current time step) and a 3-month lag (cumulative rainfall in May 2009). Multiple moving averages and lags were calculated for each time step at each precipitation and SWE station.

Groundwater data for the tool is also aggregated at a monthly timestep. As the goal of the tool is to predict groundwater levels at the beginning of next irrigation season, these values were calculated for the historic record. Continuing the example above, the “predictor” variable for July 2009 is the difference in groundwater level between April 2010 and July 2009.

The process of calculating multiple secondary variables for each time step can rapidly expand the size of the training dataset and improve predictive ability. For the initial application of the tool, changes in groundwater levels at the USGS-operated CON01 well were calculated from meteorological records at

Culebra2 (precipitation and SWE) and Manassa (only precipitation). These 3 input variables are expanded to 30 inputs when lags (1-,2-,3-,6-,and 9-month) and moving averages (3-,6-,and 12-month) are included. Additional input datasets for the model include the month (as a number) and number of days remaining until start of the next irrigation season. In total, the training dataset developed for CON01 was composed of 211 observations of 34 variables.

Step 2. Linear Regression Modeling

To establish a baseline of predictions for comparing performance of ML algorithms, a multi-variable linear regression analysis was conducted. Change in groundwater level was evaluated as a function of the 34 input variables for the initial application. Ultimately, the linear regression achieved a R^2 value of 0.5777. This will be used to compare the performance of the ML algorithms to identify if performance gains are achieved. Figure 2 shows the performance of the linear regression equation to predict the recharge water level.

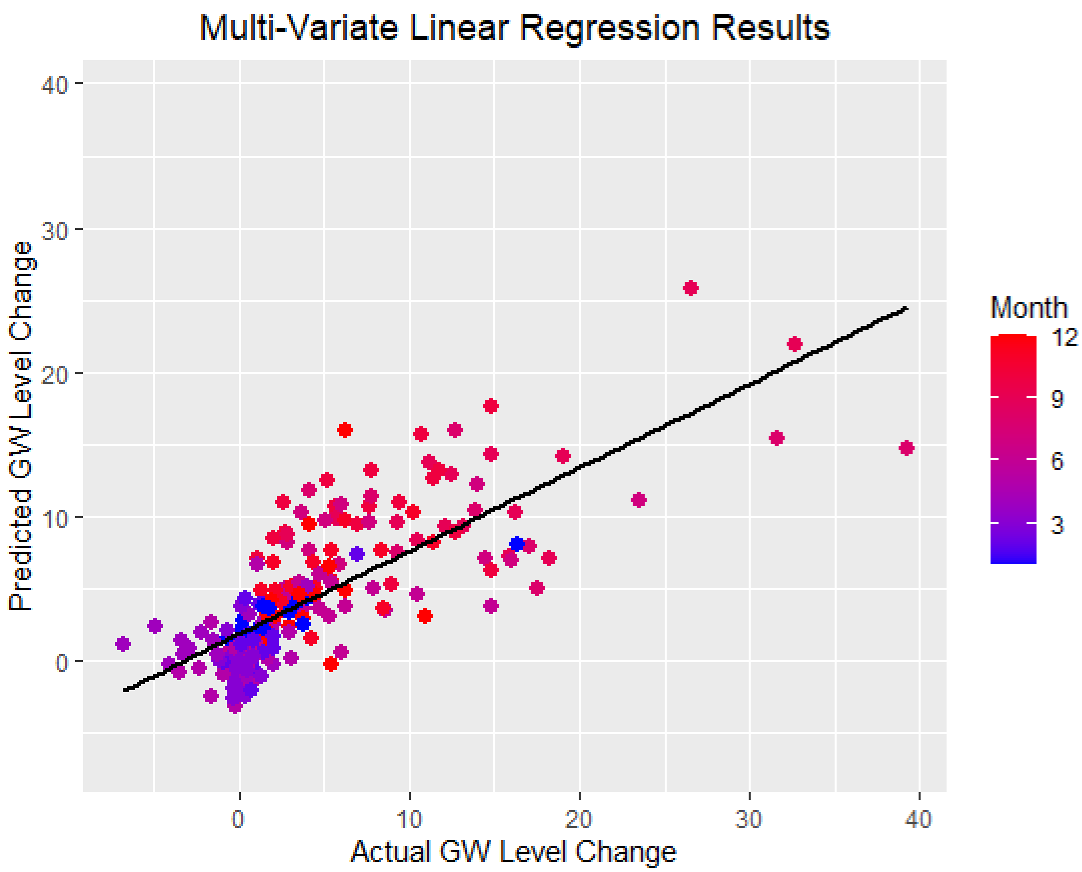

Figure 2. Scatterplot of Multi-Variate Linear Regression Prediction of groundwater level change

Step 3. ML Model Training

Machine learning requires the development of a training dataset and independent validation dataset for testing the model. For this application, the validation dataset was created by randomly sampling 20% of the input dataset. The remaining 80% was used for training.

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Machine learning refers to a large class of algorithms, each with a unique set of parameters and methods. To achieve high quality predictions, algorithms need to be trained and tested against the validation dataset. For this application, four classic ML algorithms were selected:

- Stepwise linear regression (lmSeq)
- Classification and regression trees (CART)
- k-Nearest Neighbor (kNN)
- Random Forest (RF)

During the training process, each ML algorithm is trained using 10-fold cross validation to optimize R^2 across many model runs. Table 1 shows summary statistics of the linear regression and ML models applied to the training dataset. The statistics for the ML algorithms are mean values across the trained model iterations. Figure 2 shows both the mean and range for each statistic under the ML algorithms.

Table 1. Predictive Model Comparison

Algorithm	R^2	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)
Linear Regression	0.577	4.69	--
Sequential Linear Regression	0.516	5.66	4.57
Classification and Regression Trees	0.408	5.81	4.57
k-Nearest Neighbor	0.629	7.87	6.95
Random Forest	0.728	4.01	2.93

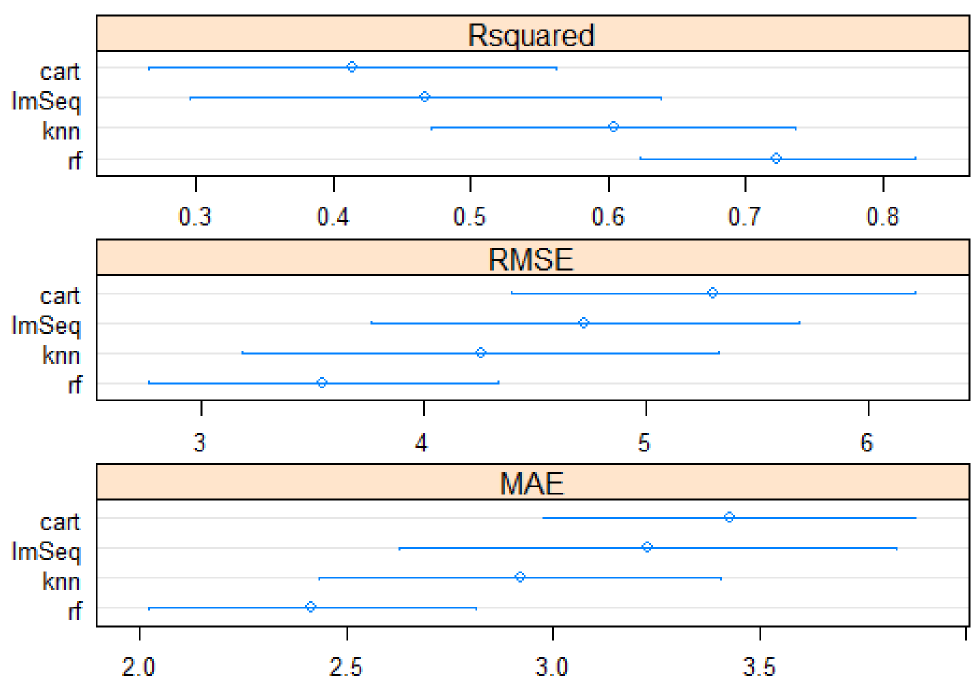

Figure 3. Box plots illustrating ML algorithm performance across three performance statistics.

Based on the findings in Table 1 and Figure 3, the Random Forest algorithm performed best among all models, with the highest R^2 and lowest RMSE and MAE. A scatter plot of predicted vs actual groundwater change from the RF algorithm is shown in Figure 4. As the best-performing ML algorithm, Random Forest was selected for validation.

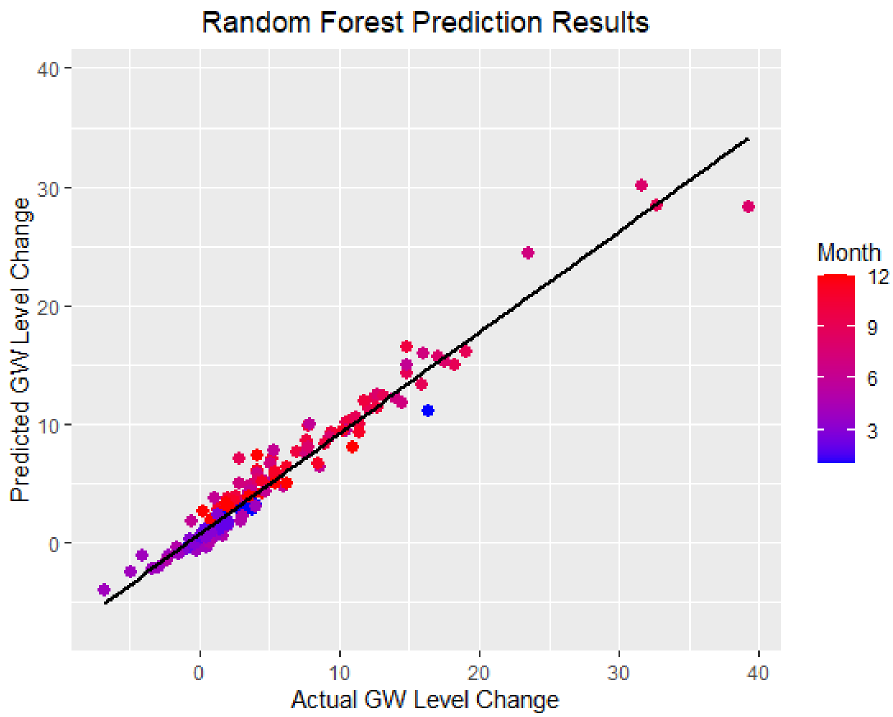

Figure 4. Random Forest ML Model prediction results

Step 4. ML Model Selection and Validation

When the trained RF algorithm was applied to the validation dataset, an R^2 of 0.757 was achieved, alongside a RMSE of 2.87 and MAE of 1.92. This indicates the RF outperforms linear regression on predicting changes in groundwater levels in the watershed. While this initial finding is encouraging, further "tuning" of RF model parameters and continued collection of observations in the DMS will increase the quality of predictions.

Initial Findings

The conceptual design of the problem i.e., predicting recharge levels based on observed water availability characteristics, seems like a promising idea for supporting aquifer management. The performance of the ML model indicates a higher degree of predictive ability than linear regression using the same inputs. This is expected, as the relationship between rainfall, SWE and groundwater levels is highly non-linear. Over time, the ML model predictions will improve in accuracy as more data is recorded and entered in the DMS, thus increasing the number of observations for training and validation of the model.

Implications and Next Steps

This predictive tool is an initial application of machine learning to the expansive groundwater dataset collected by CRSWUA. Many more insights can be likely gained through extension of the framework to alternate predictor variables and using additional input datasets.

The most straightforward next step would be to apply the model to additional wells with shorter periods of record available. In addition, Expand the tool to use the 'redundancy' in the confined aquifer measurements to enhance the prediction of next year recharge level. This would allow prediction of groundwater levels at multiple sites as a function of observed conditions throughout the study area. The model tool could also be used to fill gaps in historical records and extend the period for wells with fewer observations.

A more refined application of the tool could integrate precipitation, SWE, or streamflow forecasts (such as those published by NRCS for the Upper Rio Grande) to make more robust predictions of future groundwater levels. This would involve training the model using historic records (i.e., perfect forecast) for the study area and using forecast products for the application of year-to-year aquifer management. A rigorous implementation could integrate forecasts at multiple locations and account for uncertainty.

Independently of improving prediction accuracy, further work is needed to issue operational predictions for decision-making. While predictions can be issued in its current state, currently the tool needs to be manually run in R with a user-defined configuration. A more practical implementation would integrate the tool into the DMS and automatically process the input data and issue predictions with the most recently loaded data.