Machine Learning Approaches for Estimating Aquifer Hydraulic Properties from Step-Drawdown Pump Tests: A Case Study in Central Valley, California

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Abstract

We present a data-driven, scalable framework for estimating aquifer hydraulic conductivity by integrating step-drawdown pumping test data with well completion records using machine learning techniques. The approach applies Random Forest regression and cluster analysis to large regional datasets obtained from the California Natural Resources Agency and the Department of Water Resources Open Data platform. Specific capacity values derived from 3–72 hour pumping tests at 7,536 wells serve as the primary predictors of aquifer hydraulic behavior.

The framework enables efficient processing of heterogeneous datasets and spatially continuous estimation of hydraulic conductivity at regional scales. Unlike traditional analytical pumping test methods, which are often constrained by limited data availability and computational demands, the proposed methodology provides a consistent, data-driven alternative for estimating hydraulic properties directly from pumping and well construction data.

Results demonstrate that the machine learning framework yields robust and reproducible estimates of aquifer hydraulic conductivity at basin to subbasin scales. The approach supports the development and refinement of hydrogeologic conceptual models and provides Groundwater Sustainability Agencies with a practical tool for leveraging Sustainable Groundwater Management Act datasets to improve regional groundwater assessment and management decisions.

Keywords

Groundwater; Hydraulic conductivity; Step-Drawdown test; Pump-test methods, Machine learning; Random Forest; Cluster analysis; Specific capacity; SGMA

Introduction:

Reliable estimates of aquifer hydraulic conductivity are fundamental to groundwater modeling, water-resource management, and sustainable aquifer development. Traditionally, Transmissivity is estimated using analytical interpretations of pumping tests, such as Theis-type solutions and Step-Drawdown analysis. While effective at the site scale, these methods often require high-frequency time-drawdown data, assumptions of aquifer homogeneity, and significant manual effort, limiting their applicability for regional-scale assessments.

In California, large volumes of pumping test and well construction data have been collected and archived as part of groundwater development and regulatory reporting, particularly under the Sustainable Groundwater Management Act (SGMA). These datasets provide an opportunity to develop regional estimates of aquifer properties; however, their size, heterogeneity, and variable data quality challenge conventional analytical approaches.

Recent advances in machine learning (ML) offer new pathways for extracting hydrogeologic information from large and complex datasets. Data-driven approaches such as Random Forest regression have been successfully applied to parameter estimation, aquifer classification, and subsurface characterization. In this study, we develop a scalable ML-based framework that integrates Step-Drawdown pumping test data, well completion reports, and geospatial information to estimate hydraulic conductivity and subsurface aquifer parameters across regional aquifer systems.

The objectives of this study are to: (1) derive specific capacity metrics from Step-Drawdown pumping tests; (2) integrate pumping test data with well construction and geophysical information; (3) apply Random Forest and cluster analysis to optimize hydraulic conductivity and aquifer texture; and (4) demonstrate the applicability of the method for regional groundwater assessment and SGMA-related decision making.

2. Study Area and Data Sources

2.1 Study Area

The Central Valley aquifer occupies a region bounded approximately by 40.67° N to the north, 34.53° N to the south, 120.90° W to the west, and 120.34° W to the east. The aquifer lies between the Coast Ranges and the Sierra Nevada, extending along the Central Valley from near Red Bluff to the Bakersfield area—roughly 400–450 miles (640–720 km) north to south, with an east–west width of 20–70 miles (32–113 km). Overall, it underlies about 20,000 square miles (≈50,000 km^2) of the Central Valley floor.

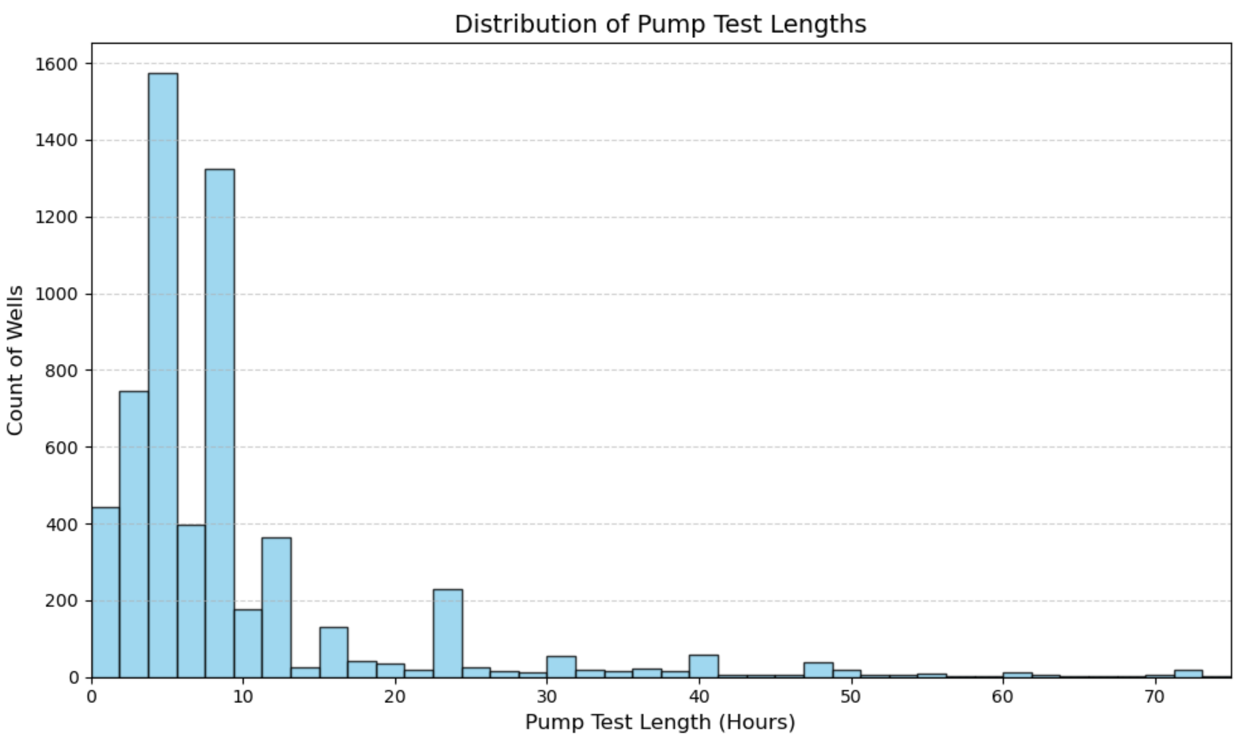
The hydrogeologic framework is composed of basin-fill alluvial sediments—including sand, gravel, silt, and clay—that accumulated within a structural trough. These deposits are exceptionally thick, locally extending several miles beneath the land surface. The aquifer system includes the major groundwater basins associated with the Sacramento River, San Joaquin River, and Tulare Lake regions, together forming one of the largest groundwater systems in the United States.

Multiple clay lenses (aquitards), collectively known as the Corcoran Clay (A-Clay through F-Clay), have been mapped across the study area. In the San Joaquin subbasin, aquifer conditions range from unconfined above the A-Clay, to semi-confined or leaky confined between the A-Clay and C-Clay, and fully confined below the E-Clay. In contrast, the Sacramento River Valley is characterized primarily by unconfined to leaky unconfined aquifer systems.

To monitor groundwater conditions, the Department has installed 181 nested monitoring wells. In addition, approximately 6,500 other monitoring wells—including active and abandoned wells—are present in the region and have been used to collect groundwater-level data. The total number of agricultural, industrial, and municipal wells is not precisely known but is estimated to be on the order of several tens of thousands.

2.2 Pumping Test and Well Completion Data

Step-Drawdown pumping test data(short-duration well tests) and well completion reports were obtained from the California Natural Resources Agency (CNRA) and the Department of Water Resources (DWR) Open Data platform. Pumping tests typically ranged from 3 to 72 hours in duration and included pumping rates (well yield), drawdown measurements, well construction details such as geospatial information, screened intervals, total depth, well yield, well yield unit of measure, test type, total drawdown, pump test length, static water level, and casing diameter. In these datasets no measurements of drawdown are taken at monitoring borehole(s).



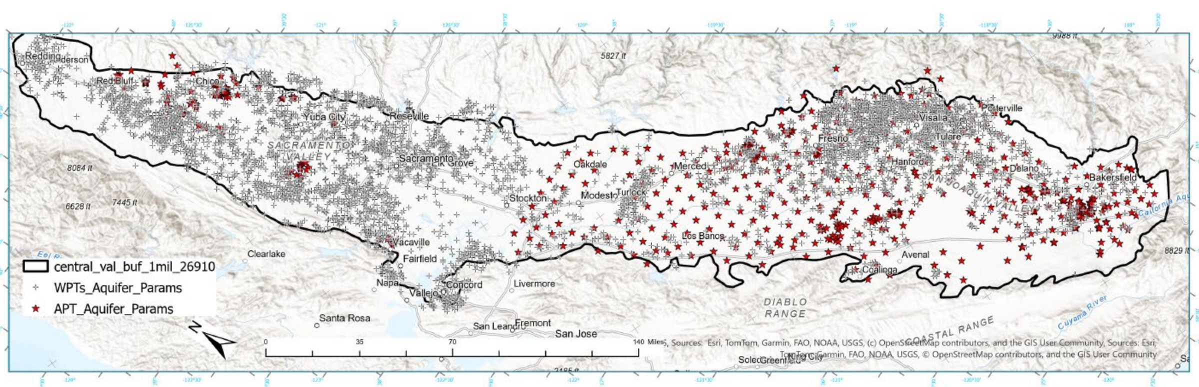
In this study, transmissivity is estimated directly from pumping tests and subsequently converted to equivalent horizontal hydraulic conductivity using screened interval thickness. When estimating **hydraulic conductivity (K_h)** for groundwater modeling and management, the reliability of the method is crucial. The most reliable method for this is **aquifer performance tests** . Aquifer Performance Tests (APTs), which involve long-duration pumping tests are often limited, local, requiring manual continuous data collection and extraction from site specific paper reports. These tests, which involve pumping a well at a constant rate for an extended period (typically 24-72 hours or longer) while monitoring water levels in both the pumping and observation wells, offer the most comprehensive and representative data. Their main advantages include characterizing a larger aquifer volume, directly measuring the aquifer's response to sustained stress, and yielding multiple essential parameters like transmissivity and storativity(S). While they are time-consuming, expensive, and require observation wells and specialized analysis, their ability to account for aquifer heterogeneity makes them the most reliable choice for detailed aquifer characterization.

Short-duration well tests, such as slug and Step-Drawdown tests, provide a rapid and cost-effective alternative to pumping tests. These tests involve an instantaneous change in water level followed by observation of recovery and are commonly used for preliminary site characterization or for estimating hydraulic conductivity in fine-grained materials and discrete well-screen intervals. As a result, they yield hydraulic conductivity estimates representative of the immediate vicinity of the well screen.

However, the principal limitation of short-duration tests is their restricted spatial representativeness. They characterize only a small volume of the aquifer surrounding the well and therefore may not adequately capture heterogeneity at larger scales. In addition, these tests generally do not provide reliable estimates of S, and reported hydraulic conductivity values can vary by up to an order of magnitude relative to results obtained from pumping tests.

To address these limitations, we adopted a successive approximation approach proposed by Aqtesolv Inc. This method initiates analysis with an assumed S value and iteratively solves the governing equations using the full time–drawdown dataset, eliminating the need for traditional curve-matching procedures. By applying this approach uniformly across all short-duration pumping tests, we simultaneously estimated transmissivity and storativity in a consistent and automated framework.

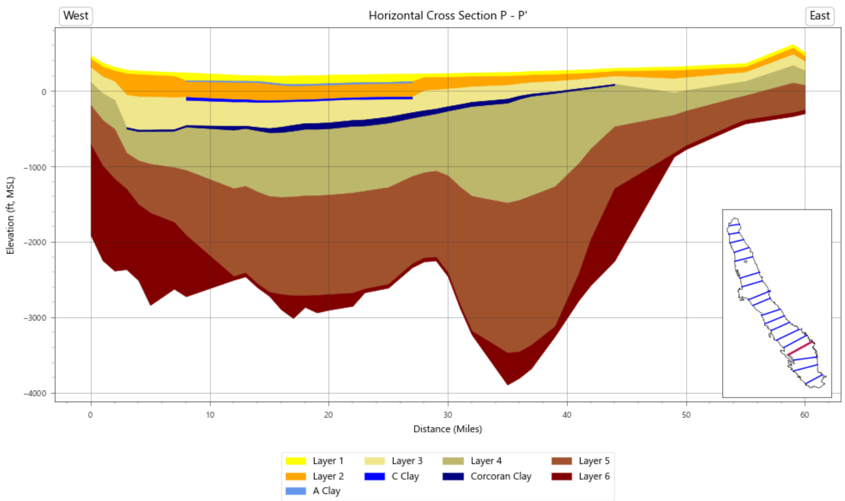
Figure 1: location of short-duration (in red) vs. long-duration pump-tests (in black):



2.3 Ancillary Geospatial and Geophysical Data

Additional datasets included lithologic descriptions, and spatial attributes derived from geophysical surveys and GIS-based layers. These data were used to support aquifer type mapping and spatial interpolation of hydraulic properties. In the study area hydrogeologic setting varies from unconfined (above A-Clay) to leaky unconfined/ confined (between A-Clay, B-Clay, C-Clay, D-Clay) and confined system below E-Clay(Corcoran Clay).

Figure 2- location of clay aquitards and model layers.



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3. Methods

3.1 Specific Capacity Estimation

Specific capacity ($Sc = Q/s_w$) was calculated from Step-Drawdown pumping tests as the ratio of pumping rate(well yield in gallons per minute) to observed drawdown (in foot). Pumping test preprocessing and quality control were performed using custom Python scripts developed with the SciPy library.

3.2 Cluster Analysis and removing outliers

To discover hidden spatial patterns in well performance, the data was cleaned and scaled before applying DBSCAN, a density-based clustering algorithm that identifies natural groupings while isolating noise. The model utilizes two primary parameters—Epsilon (eps = 0.5) to define search radius and Min Samples (25) to ensure cluster robustness—with the optimal distance threshold determined via a K-distance plot. This approach effectively filters out anomalous tests and visualizes geographic-performance relationships through spatial mapping.

Table 1: DBSCAN parameters specified in cluster analysis.

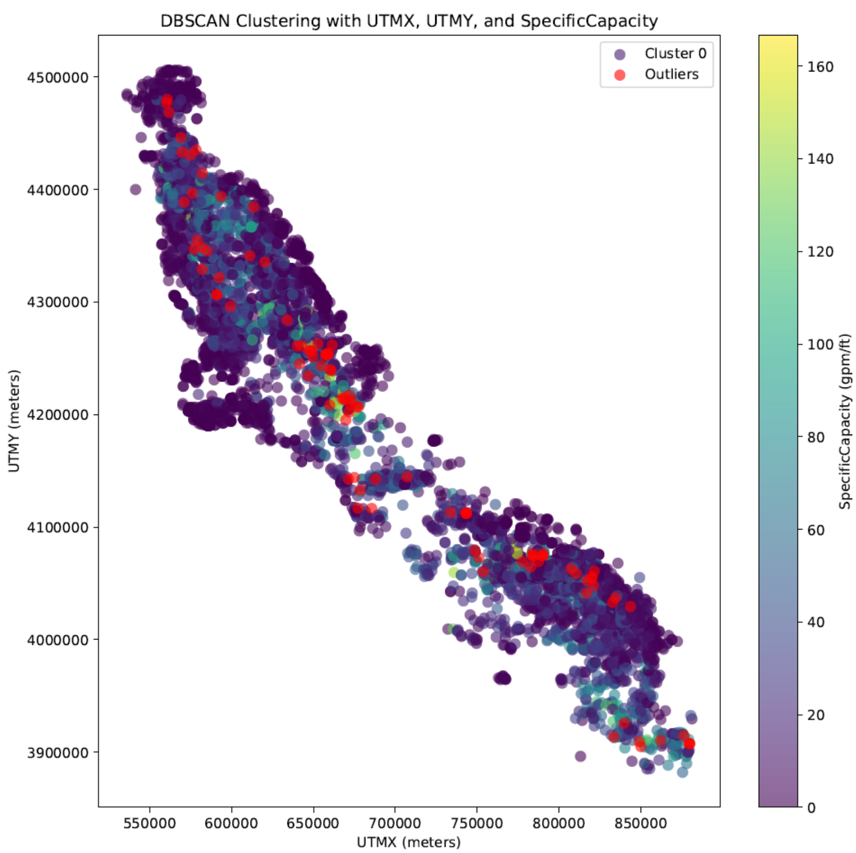
Parameter	Setting	Function
Epsilon	0.5	The maximum distance allowed between two points to be considered neighbors.

Parameter	Setting	Function
Min Samples	25	The minimum number of points required to form a dense, legitimate cluster.
Outliers	Label -1	Points that do not meet density requirements, isolating unique or erroneous data.

Computational Implementation of Cluster Analysis and Random Forest in Python

We made use of NearestNeighbors module from sklearn to generate this plot. Since our min_samples is set to 25, we will look at the distance to the 25th nearest neighbor (k = 25).

Figure 5- **Spatial maps** of specific capacity values and outliers(in red):



3.3 Feature Engineering and Data Integration

Predictor variables included specific capacity, well depth, screened interval length, lithologic texture indicators, and spatial attributes. All datasets were harmonized to a common spatial reference system and integrated into a unified analysis database.

Previous methods rely heavily on specific capacity, which is appropriate for short-duration tests but sensitive to well efficiency, partial penetration, and leakage effects.

Although we're focusing on single-well pump tests and not directly employing standard curve-matching techniques, it's still possible to utilize curve-matching approaches. For individual drawdown data, we can iteratively apply exact approaches (such as Cooper-Jacob; Thies; Neuman, Moench, Sterltsova, Hantush; Boulton), in reverse. By using initial estimates for transmissivity (T) and storativity (S), we can programmatically iterate through the data to determine the correct scaling factor. This is a significant advantage over other empirical methods (such as Batu, Driscoll, and Razack and Mace) that rely on a fixed scaling factor, as our approach allows for a fine-tuned scaling factor for each well pump test dataset. This can be achieved using coding methods and Python libraries (SciPy), specifically employing successive approximation algorithms (such as Nelder-Mead SSA) to solve for transmissivity (T).

Table 2: Pump Test analysis approaches used

Method (Primary Author/Tool)	**Aquifer Type / Condition**	**Key Phenomenon / Storage**	**Application Notes**
Cooper & Jacob (1946)	**Confined (Infinite)**	Theis/Standard Assumptions	The basic, widely used graphical **straight-line method** for long-duration tests.
Hantush & Jacob (1955)	**Leaky Confined**	**Leakage** (from semi-confining layer)	Analysis when water enters the main aquifer from adjacent layers.
Theis (via AQTESOLV)	**Confined (Infinite)**	Standard Theis Solution	Fundamental solution for non-equilibrium flow; often a starting point for analysis.
Boulton (1963)	**Unconfined (Water Table)**	**Delayed Yield/Delayed Gravity**	One of the earliest solutions to account for the slow drainage from the unconfined zone.
Streltsova (1972b)	**Unconfined (Water Table)**	Unsteady Radial Flow	Focuses on the complex nature of unsteady flow in unconfined settings.
Neuman (1975)	**Anisotropic Unconfined**	**Delayed Gravity Response**	The industry standard for unconfined aquifers, separating **early-time** (confined) and **late-time** (delayed yield) behavior.
Moench (1985)	**Confined/Leaky (Large Diameter Well)**	**Borehole Storage** & **Storative Skin/Leaky Layers**	Excellent for short-duration tests and large-diameter wells; accounts for complex conditions near the well.
Barlow & Moench (WTAQ v2)	**Confined & Water Table**	**Drainage from Unsaturated Zone**	Computer program combining modern solutions (like Moench/Neuman) for complex field data analysis.
Mace (1997)	**Karst Aquifer**	T from **Specific Capacity**	Empirical/analytical methods to estimate Transmissivity (T) from simple short-duration tests, often in highly heterogeneous systems.
Razack & Huntley (1991)	**Alluvial Aquifer (Heterogeneous)**	T from **Specific Capacity**	Focuses on robust T estimation from Specific Capacity, particularly valuable in complex alluvial settings.

Driscoll (1986)	**General**	T from **Specific Capacity**	Classic reference focusing on practical aspects like **well-skin effect** and well efficiency, which affect all test results.
Batu (1998)	**General**	T from **Specific Capacity**	A comprehensive guide and textbook; provides context for nearly all analytical methods.
Nelder & Mead (1965)	**Optimization/Curve Fitting**	**Function Minimization**	A general-purpose **numerical optimization algorithm** used by modern software (like AQTESOLV) to automatically fit analytical solutions to observed data.

3.4 Machine Learning Framework

Targeted Optimization and Latent Structure Discovery

To advance the goal of **simplifying complex datasets** and **revealing hidden structures**, the workflow transitions into a sophisticated phase of data recovery and targeted predictive modeling.

Data Imputation

The process begins by addressing gaps in the dataset through **KNN Imputation**. Missing transmissivity values are estimated by identifying natural associations between "neighboring" wells in the feature space. By weighing these neighbors based on their distance, the model fills data gaps using geospatial coordinates and physical well characteristics. This ensures a complete and continuous dataset, transforming fragmented raw data into a robust foundation for analysis.

Sources of blank Data: A total of 2,149 Cooper–Jacob transmissivity estimates failed to satisfy the $u < 0.01$criterion. Additionally, 1,992 estimates did not converge successfully when applying the Nelder–Mead simplex algorithm to the Moench, Hantush, Sterltsova, and Papadopoulos methods.

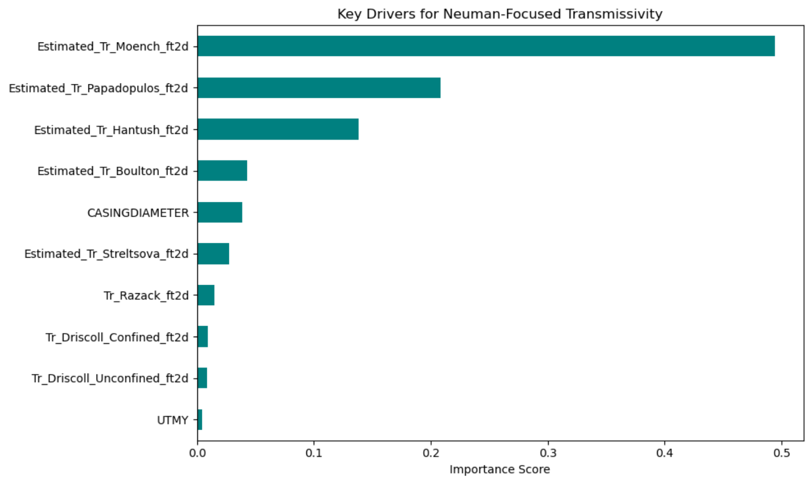
Targeted Random Forest Modeling

Following data completion, the focus shifts to **exploratory analysis** by centering on the **Neuman Method** as the primary ground truth. A **Random Forest Regressor** is employed to learn the complex, non-linear relationships between the well's physical attributes and this specific analytical target. This ensemble learning approach effectively handles high-dimensional data to produce a **Neuman-Optimized Transmissivity** value. This refined metric provides a more reliable interpretation of the subsurface structure than any single raw measurement, effectively "smoothing" the noise inherent in individual field tests.

Feature Importance Analysis

To identify which variables are the primary drivers of these results, we utilize **Feature Importance** analysis. In high-dimensional datasets, not all variables contribute equally to the hidden structure. By analyzing the **"Gini importance"** or **"mean decrease in impurity,"** we mathematically determine the influence of each input. This allows us to confirm whether a well's **SpecificCapacity** is a more significant predictor of transmissivity than its total depth or geographic position, revealing the dominant physical laws governing the aquifer.

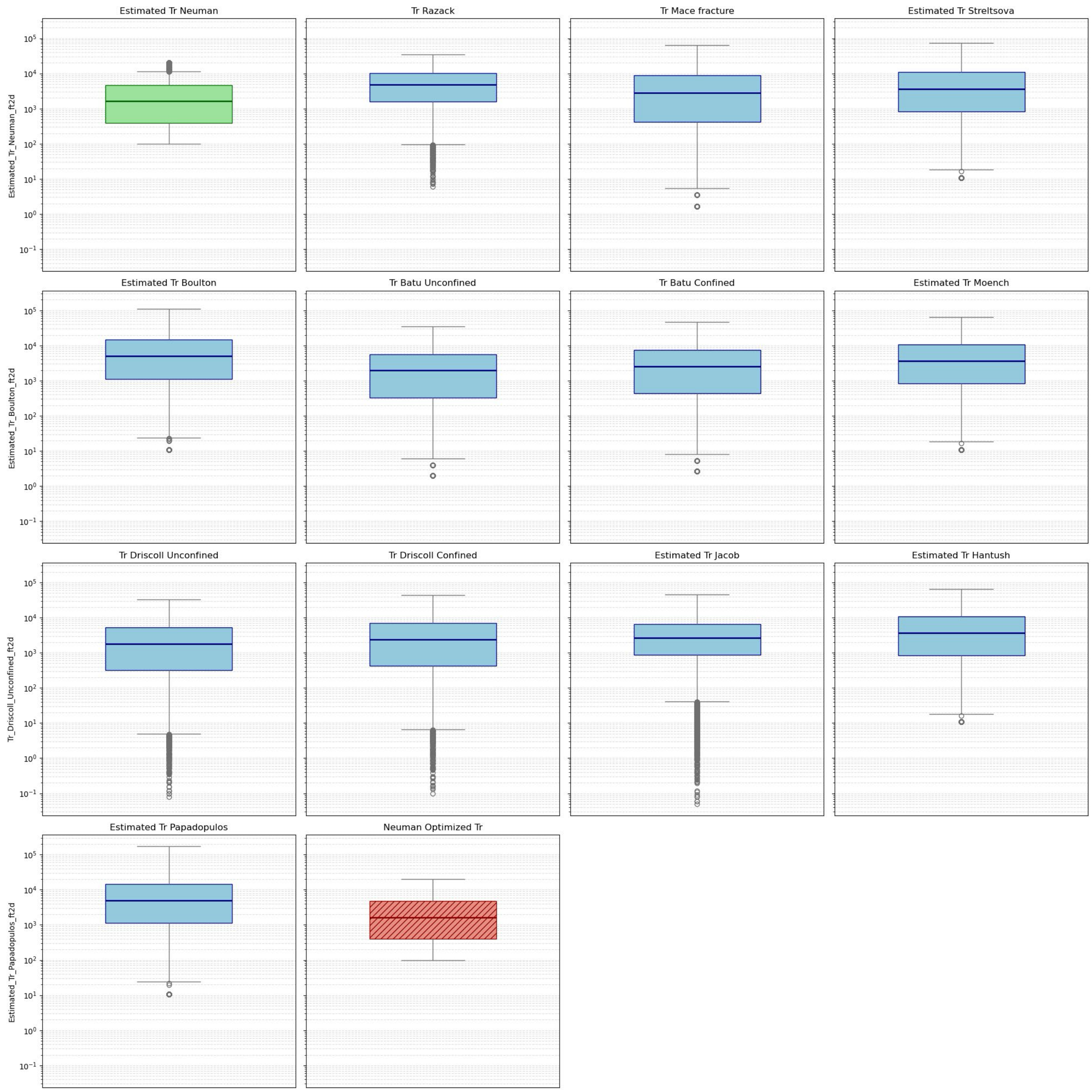
Figure 7- Key Drivers for prediction of transmissivity and optimization of Neuman approach



Visualizing Latent Distributions

The final stage of this simplification involves comparing the optimized results against eleven legacy analytical methods using **logarithmic box plots**. Because hydraulic properties vary across multiple orders of magnitude, the log-scale visualization reveals the latent structure of the data distribution. By highlighting the **Neuman-Optimized** results alongside the original estimates, we can visually verify how the model has reduced variance and reclaimed consistency from a historically complex and "noisy" dataset.

Figure 8- Box Plots comparison of all pump-test methods vs optimized using ML.



How to Implement the Analysis

We can extract these insights directly from your trained rf_model using the following logic:

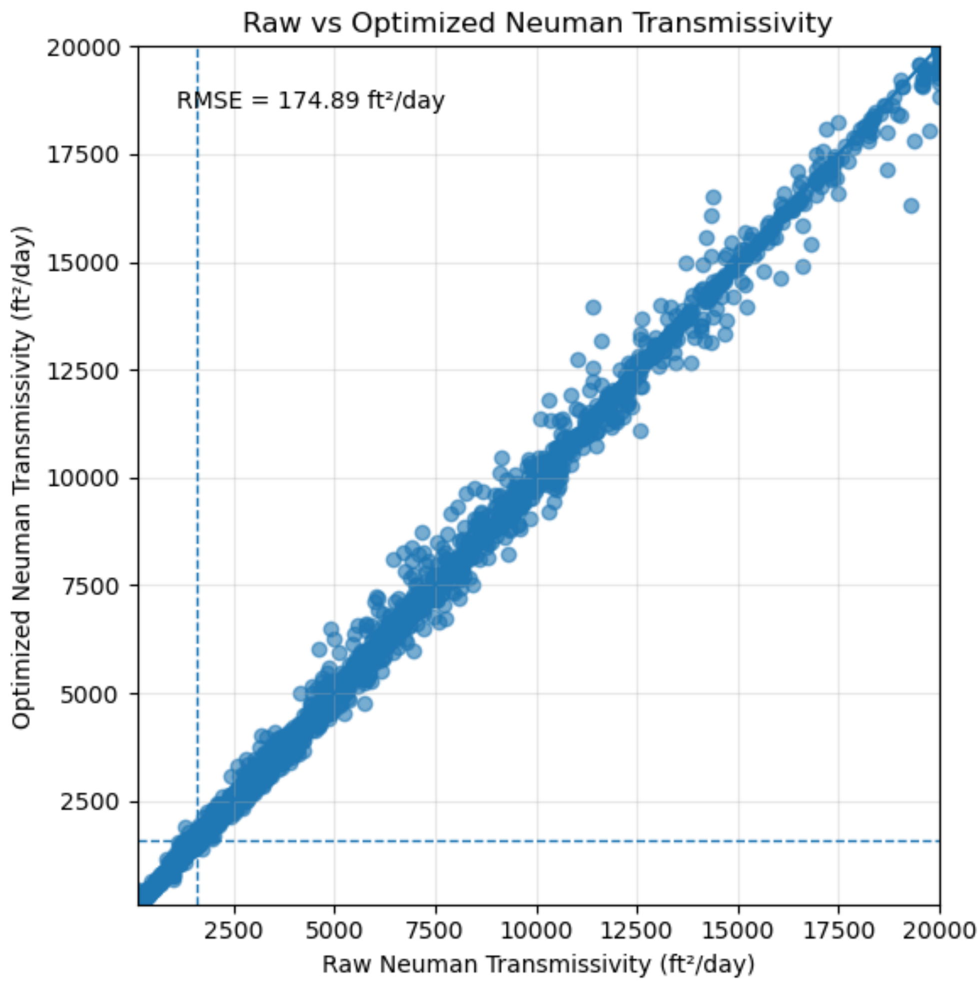
The modeling workflow was refined to perform a targeted optimization focused specifically on transmissivity estimates derived from the Neuman method. In this step, the Neuman-based transmissivity (Estimated_Tr_Neuman_ft2d) was designated as the prediction target, while the input features consisted of the full set of processed explanatory variables along with transmissivity estimates from alternative methods, excluding the Neuman value itself. This approach allowed the model to learn relationships between site characteristics and complementary analytical estimates while avoiding information leakage from the target variable.

Model training was restricted to records for which Neuman transmissivity values were available. Rows with missing Neuman estimates were excluded to ensure the integrity of the supervised learning process. The resulting dataset was then divided into training and testing subsets, with 80 percent of the data used for model training and 20 percent reserved for independent evaluation. A fixed random seed was applied to ensure reproducibility of the data split and subsequent results.

An ensemble learning approach was implemented using a Random Forest regressor, selected for its robustness to nonlinear relationships and its ability to handle complex interactions among predictor variables. The model was trained using 100 decision trees, providing a balance between predictive accuracy and computational efficiency. This ensemble framework enabled the model to capture patterns inherent in the Neuman-based transmissivity estimates that may not be fully described by any single analytical method.

Once trained, the optimized Random Forest model was applied to the entire dataset to generate improved transmissivity predictions. These predictions were stored as a new variable, representing Neuman-optimized transmissivity values for all wells, including those lacking direct Neuman estimates. This process effectively extended Neuman-based transmissivity information across the dataset in a consistent and data-driven manner, supporting broader spatial and statistical analyses.

Figure 10- Optimized Transmissivity derived from ML vs Estimated from exact equation:



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4. Results

4.1 Model Performance

Random Forest models demonstrated strong predictive performance across multiple validation datasets. Performance metrics such as coefficient of determination (R^2 = 0.9983) and root-mean-square error (RMSE = 174.89) indicate that the ML approach captures key hydraulic trends observed in the pumping test data. Here are some statistical analyses for predicted Transmissivity versus raw Transmissivity data:

Table 3- statical analysis of Random Forest results

Parameters statistically analyzed	values
Median_Neuman	1577.634
Median_ML	1581.32
IQR_Neuman (IQR = Interquartile Range. IQR= Q75-Q25;	4251.97

Q25 (1st quartile); Q75 (3rd quartile))	
IQR_ML	4231.65
RMSE (Root Mean Square error)	174.89
R^2	0.9983

Table 4- statical analysis of aquifer parameters for all six layers of C2VSimFG model

Layer	K_h (min)	K_h (max)	K_h (mean)	K_h (median)	K_h (std)
1	0.13	164.01	35.40	26.40	27.86
2	0.11	172.22	33.81	27.15	24.23
3	0.02	147.12	30.87	24.37	22.60
4	0.03	162.84	21.65	19.12	14.33
5	0.01	74.78	13.80	11.40	9.56
6	0.01	50.88	6.43	5.26	5.64
avg	0.05	128.64	23.66	18.95	17.37
Layer	**Transmissivity** (min)	**Transmissivity** (max)	**Transmissivity** (mean)	**Transmissivity** (median)	**Transmissivity** (std)
1	4.26	9326.97	1653.30	1276.11	1240.53
2	6.20	23873.87	3899.71	3100.27	3180.98
3	2.30	36715.59	5569.32	4659.36	4233.89
4	4.04	68748.06	7130.62	5905.62	5945.25
5	2.03	52952.99	7234.71	5668.27	6037.16
6	2.54	67128.74	4750.78	2464.09	6166.35
avg	3.56	43124.37	5039.74	3845.62	4467.36

Layer	S_c (min)	S_c (max)	S_c (mean)	S_c (median)	S_c (std)
1	1.14E-05	2.52E-03	1.82E-04	1.16E-04	1.61E-04
2	1.00E-09	3.06E-02	2.11E-04	1.13E-04	1.03E-03
3	1.00E-09	4.11E-02	2.81E-04	1.14E-04	1.68E-03
4	1.00E-09	5.84E-03	1.40E-04	1.14E-04	2.16E-04
5	1.00E-09	8.79E-03	1.42E-04	1.13E-04	3.08E-04
6	1.90E-05	4.83E-03	5.37E-04	1.15E-04	7.34E-04
avg	5.05787E-06	1.56E-02	2.49E-04	1.14E-04	6.87E-04

Layer	K_v (min)	K_v (max)	K_v (mean)	K_v (median)	K_v (std)
1	0.007	8.200	1.770	1.320	1.393
2	0.005	8.611	1.691	1.358	1.211

3	0.001	7.356	1.543	1.219	1.130
4	0.002	8.142	1.083	0.956	0.716
5	0.000	3.739	0.690	0.570	0.478
6	0.001	2.544	0.322	0.263	0.282
avg	0.003	6.432	1.183	0.948	0.868

Layer	S_s (min)	S_s (max)	S_s (mean)	S_s (median)	S_s (std)
1	2.28E-07	0.000147157	4.03E-06	2.34E-06	5.09E-06
2	3.32E-12	0.001057203	2.19E-06	1.05E-06	1.07E-05
3	2.75E-12	0.00082537	1.59E-06	6.58E-07	8.14E-06
4	1.22E-12	5.57E-05	7.06E-07	3.93E-07	2.44E-06
5	2.56E-12	6.79E-05	4.73E-07	2.43E-07	1.96E-06
6	2.84E-08	9.56E-05	2.45E-06	5.93E-07	6.23E-06
avg	4.26657E-08	0.000374814	1.90555E-06	8.79549E-07	5.76583E-06

Layer	S_y (min)	S_y (max)	S_y (mean)	S_y (median)	S_y (std)
1	0.010	0.150	0.074	0.075	0.040
2	0.005	0.159	0.102	0.108	0.037
3	0.005	0.154	0.115	0.126	0.035
4	0.004	0.157	0.118	0.132	0.037
5	0.008	0.161	0.117	0.131	0.037
6	0.004	0.181	0.098	0.102	0.042
avg	0.006	0.160	0.104	0.113	0.038

4.2 Spatial Distribution of Hydraulic Conductivity, Transmissivity and Specific yield

The spatial distribution of estimated hydraulic conductivity (K_h) exhibits systematic patterns that align closely with established hydrogeologic features of the Central Valley. High-conductivity zones are consistently associated with coarse-grained alluvial fan deposits and ancestral river channels, whereas lower values correspond to fine-grained lacustrine deposits or regional confining units. Notably, the spatial trends for **specific yield (S_y)** closely mirror those of hydraulic conductivity; this correlation is expected in porous media, where coarser materials (like gravels and sands) typically exhibit both higher permeability and higher drainable porosity compared to finer-grained silts and clays.

Figure 11- **Spatial maps** of Hydraulic conductivity by model layer:

Kxy ft/d (APT and Step-drawdown-tests)

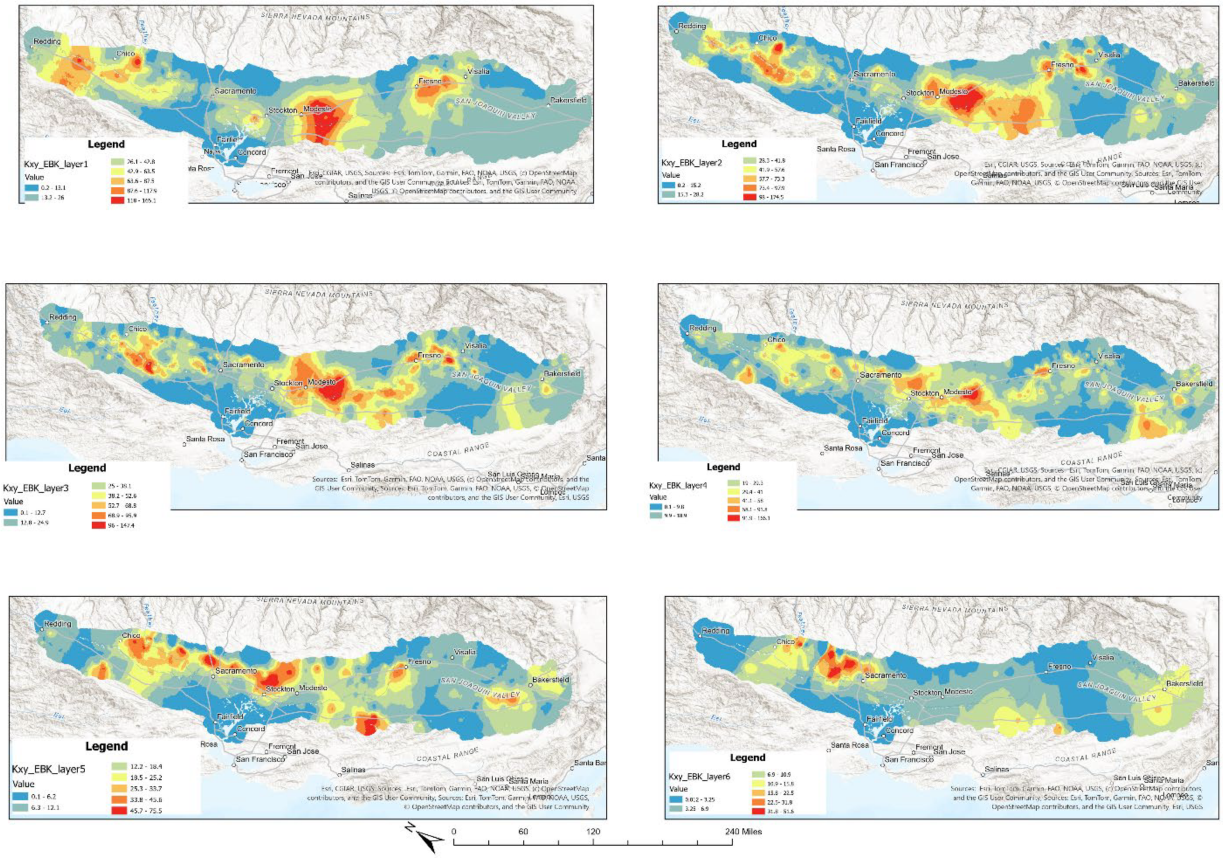


Figure 12- **Spatial maps** of specific yield by model layer:

Specific Yield [%] values (APT and Step-drawdown-tests)

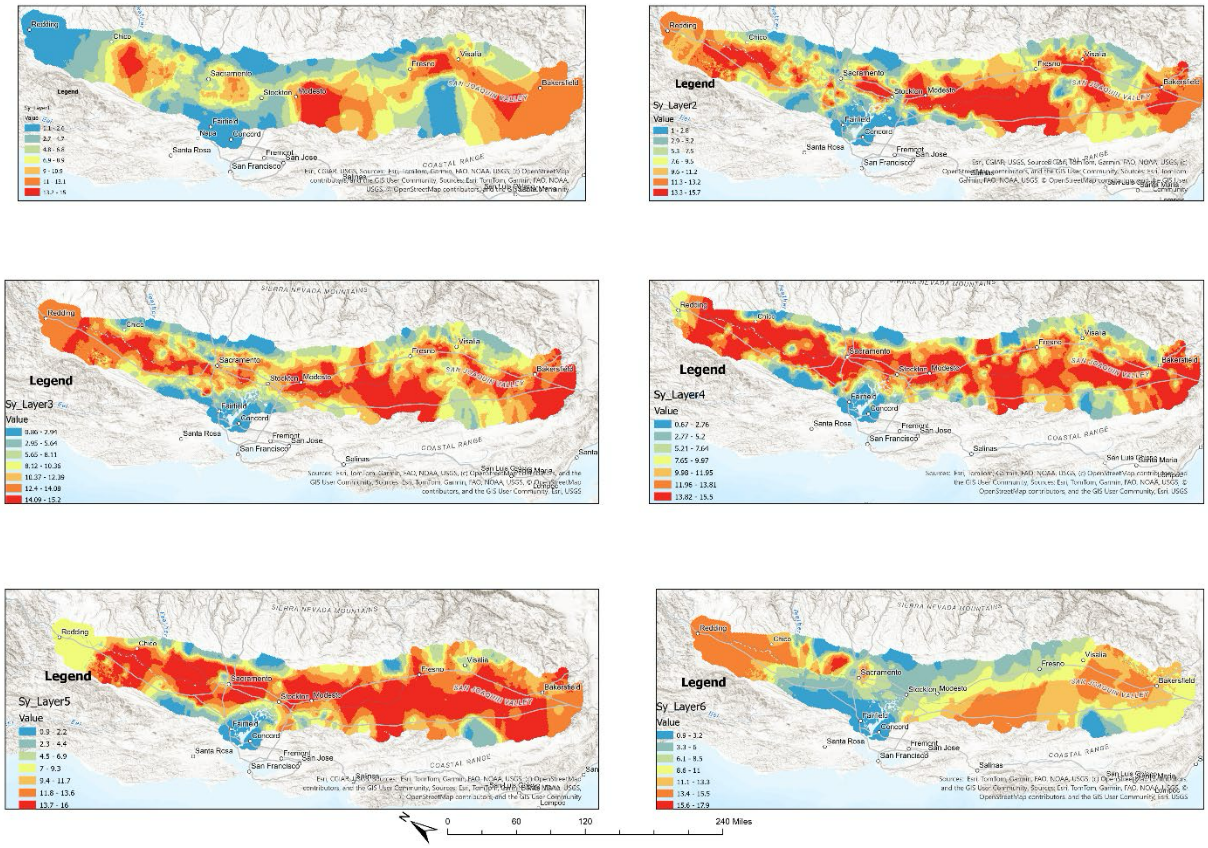
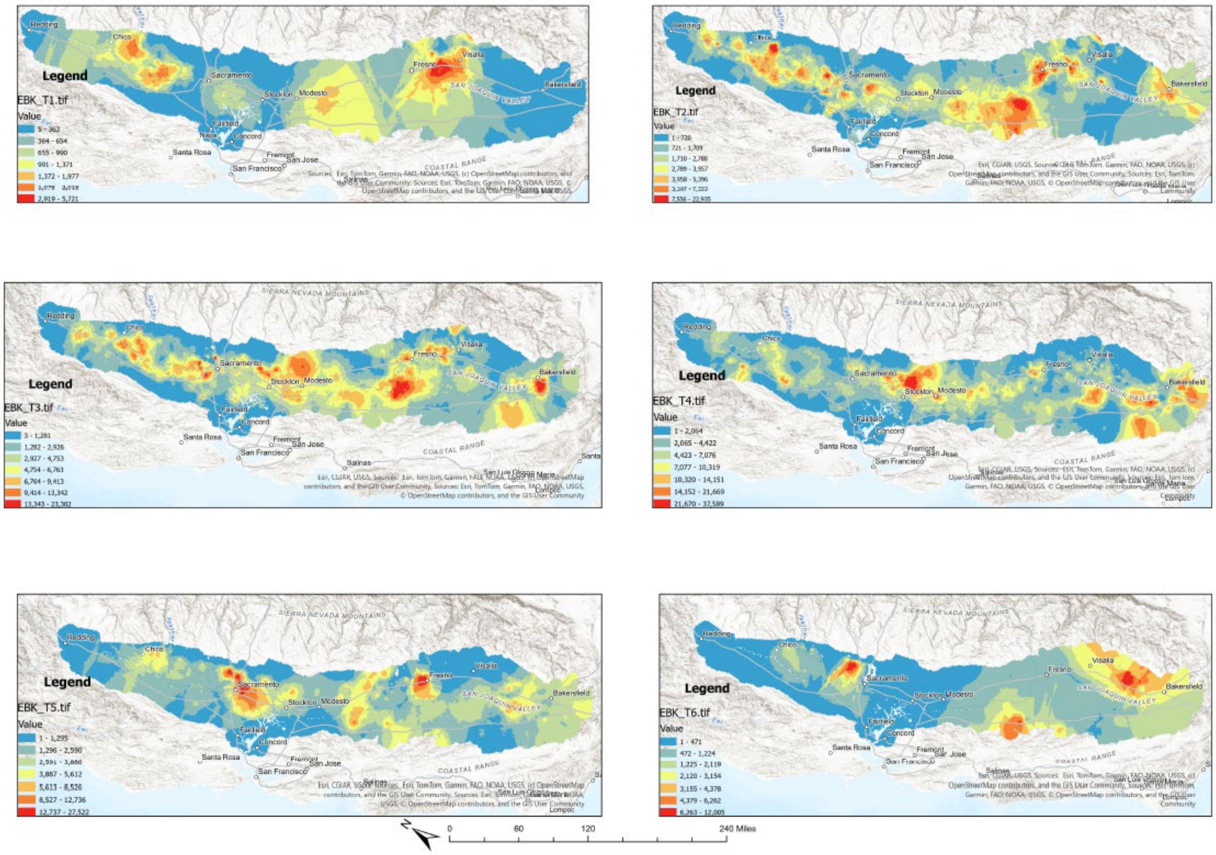


Figure 13- **Spatial maps** of Transmissivity by model layer:

Transmissivity ft2/d (APT and Step-drawdown-tests)



4.3 Where the model performs poorly

Estimations for the vertical hydraulic conductivity (K_v) and the storage coefficient or storativity (S) are currently suboptimal. Because the existing framework relies on the Neuman approach—which typically presets K_v at 5% of K_h —the model lacks the flexibility required to calculate these parameters with high precision. While the proposed ML framework excels at predicting horizontal hydraulic conductivity (K_h), deriving the *S* from specific capacity data remains challenging. The value of S is highly sensitive to the duration of the test and the distance to observation wells. Since short-duration pumping tests are typically conducted as single-well tests without separate monitoring points, the spatial data required to reliably calculate S is inherently missing.

However, regional groundwater model sensitivity is generally lower for the S compared to K_h; therefore, the proposed approach remains promising as these parameters can be further refined during the model calibration phase. Refining the estimation of K_v remains a task for future research, focusing on identifying analytical models capable of estimating vertical anisotropy with higher accuracy.

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5. Discussion

The results demonstrate that machine learning provides a practical alternative to traditional pumping-test analysis for large-scale groundwater assessments. By leveraging specific capacity and well construction data, the proposed framework bypasses the limitations of analytical solutions that require detailed time-drawdown records and restrictive assumptions.

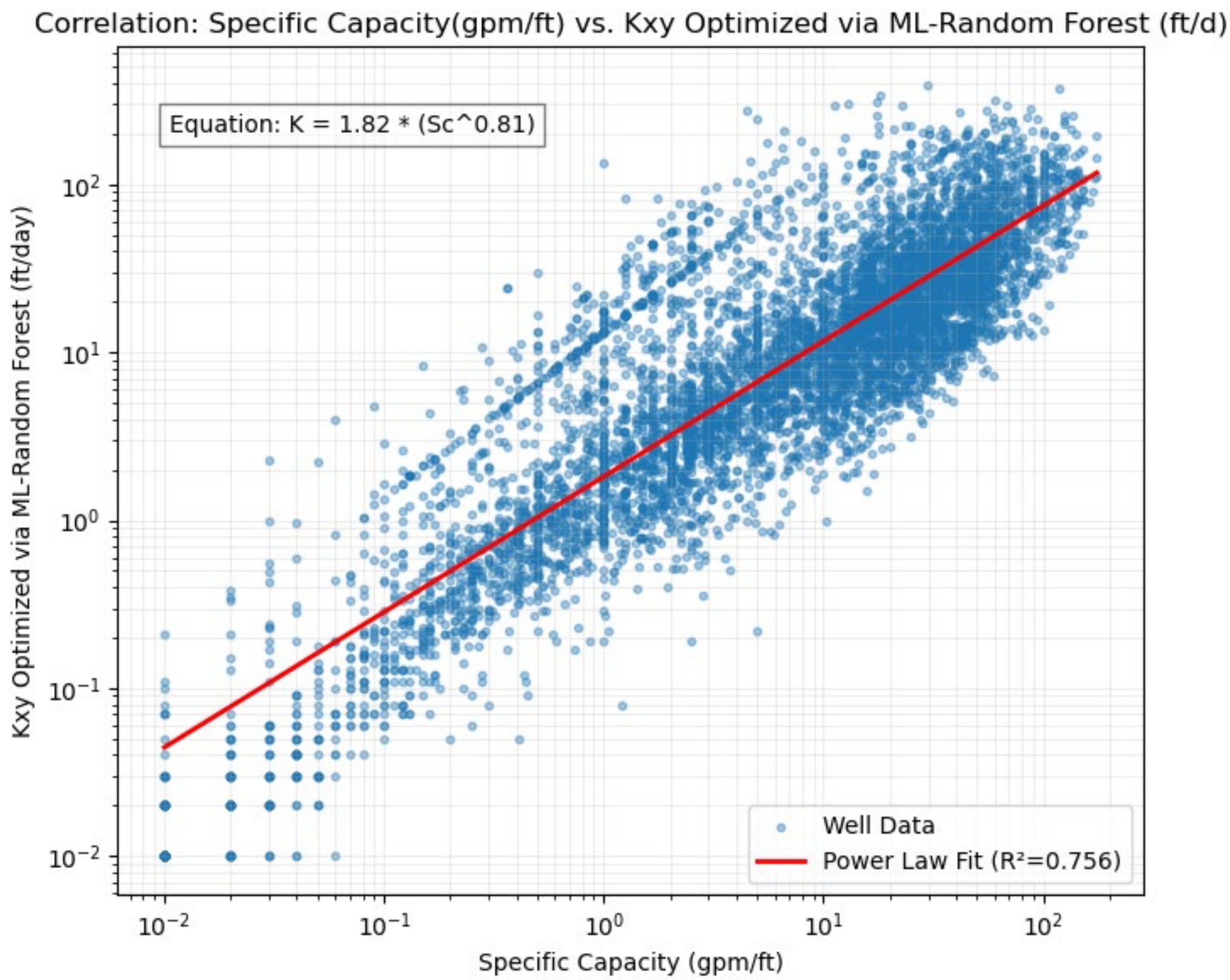
Uncertainty in the ML-derived estimates arises from data quality, spatial sampling density, and heterogeneity in well construction practices. Nevertheless, the consistency of spatial patterns and alignment with known hydrogeologic features suggests that the approach is suitable for regional conceptual model development and preliminary parameterization of groundwater models.

Previously constrained to conceptual understanding, the utility of capacity-specific data, GSAs now possess the capability to deploy this data via standardized methods and machine learning frameworks.

Machine learning should be viewed as a complement to, rather than a replacement for, Aquifer Performance Tests (long-duration pump tests in short APTs) , which remain the industry standard for reliability. In the Central Valley, physical and hydraulic boundaries—such as the Sacramento River or the Sierra Nevada—often necessitate prioritizing early-test data to avoid the interference of boundary effects like leakage, decreasing saturated thickness, or neighboring pumping. Consequently, during tests impacted by delayed yield or leakage, the early-time data typically offers the most accurate estimation of hydraulic conductivity (K values).

While traditional analytical methods struggle with the non-linearity of well-bore skin effects and partial penetration, the Random Forest architecture inherently accounts for these by treating well construction parameters (screen length, diameter) as primary features. This effectively 'normalizes' the specific capacity data, allowing for a more accurate extraction of the underlying formation conductivity (K) than is possible with rigid constants like the Driscoll method.

Figure 14- correlation plot between Specific Capacity (Sc) and optimized hydraulic conductivity



6. Implications for Groundwater Management

The developed workflow offers Groundwater Sustainability Agencies with a scalable and reproducible method for estimating aquifer hydraulic properties using existing SGMA datasets. The resulting texture maps and hydraulic conductivity fields can support basin characterization, numerical model development, and evaluation of groundwater management scenarios.

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7. Conclusions

This study presents a machine-learning-based framework for estimating aquifer hydraulic conductivity from Step-Drawdown pumping tests and well completion data. The integration of Python-based data processing, Random Forest regression, and cluster analysis enables efficient regional-scale assessment of aquifer properties. The methodology provides a valuable complement to traditional hydrogeologic analysis and supports data-driven groundwater management under SGMA.

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