Groundwater Monitoring&Remediation

Column

Leveraging Hydrogeologic-Based Data—Reduce, Repurpose, Reimagine

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Introduction

Hydrogeologic-focused data (e.g., groundwater levels, precipitation, hydraulic conductivity values) collected from environmental, water resources, and remediation projects are essential building blocks for site characterization, evaluation, and design. While these data may be initially obtained for specific objectives, the assemblage of this information into big data sets to gain additional insights via data transformation or advanced analytical methods is often underutilized, if not completely overlooked. This is particularly true when data are collected solely for compliance purposes without consideration of using the data to further inform and refine the conceptual site model (CSM). Leveraging these big data sets to be "mineable" to develop more robust CSMs within a hydrostratigraphic flux framework (an approach where geologic information is integrated and interpreted primarily in the context of groundwater flow) is even more critical today to address the need for resilient and cost-effective remediation strategies that meet the challenges posed by emerging contaminants. To do this effectively groundwater practitioners must embrace data science principles, which will require involvment of specialized data analysts, application of enhanced visual presentation tools, and use of stakeholder-friendly data sharing platforms (Horst et al. 2022).

Robust CSMs, which ultimately lead to successful project outcomes, are data rich and adaptive, or "living," and, as such, discourage risky shortcuts in contaminant characterization and remedial design (Payne et al. 2008). Furthermore, the common occurrence of sites or projects changing ownership over time can easily lead to the loss or underutilization of valuable historical data. Integrating these data within an established, centralized platform and workflow enhances efficiency, standardizes data use, facilitates knowledge transfer, and streamlines data management efforts, thereby *reducing* the overall effort and redirecting time toward data interpretation.

The technical advancements in big data concepts (storing, accessing, transforming, visualizations, and artificial intelligence [AI]) should support hydrogeologic-focused data or other data types to better inform on site characterization without overwhelming practicality. Establishing goals to leverage data sets for *repurpose* can provide further insights. For example, automating the analysis of existing multiple soil particle-size distribution data or low-flow groundwater sampling data through a common data platform can be used to quickly characterize and/or provide useful insights on permeability distribution, design criteria, and well performance. This data repurposing takes advantage of (historical, current, and future) data collection efforts and unlocks additional data potential.

The development and use of AI as a tool for managing "big data" is gaining momentum among groundwater practitioners to enhance the utilization of diverse data types. While the underlying conditions for effective data processing in the groundwater sciences are suitable for codification by AI (i.e., explicit knowledge, objective, logical, and easily transferable), tacit knowledge, rooted in personal experiences and observations, presents a unique storage and management challenge. Training AI tools may help bridge this gap by extracting new insights based on tacit knowledge from subject matter experts. This has the potential to enrich data-driven interpretations that include the widest possible background considerations, weighted for importance. The integration of AI tools by using this approach can *reimagine* the way we collect and analyze knowledge to unlock opportunities in efficiency and innovation.

By centralizing and streamlining data management efforts, organizations can reduce inefficiencies and redirect efforts toward high-value interpretations. Development and application of automated data processing using established protocols, without sacrificing data quality, further supports this expansion of knowledge use. By integrating AI tools and adopting methods that connect explicit and tacit knowledge, the application of big data analytics can vastly enhance our decision-making capabilities as groundwater practitioners. Through the themes of *reduce*, *repurpose*, and *reimagine*, organizations can more effectively unlock

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the full potential of hydrogeologic data to drive efficiency and foster innovation.

To complement the written text, we have recorded an audio summary that is included as downloadable Supplemental Information where we summarize the main features of this article and discuss what we consider key takeaways and implications (Audio S1).

What Data Are at Our Fingertips?

Typical site hydrogeologic data collection includes many data types focused on soil and aqueous media. Routine and standardized sampling requirements continue to produce data that have been historically, or are currently, managed electronically or in physical paper format but have often been stored as subsets in different repositories. For example, common data types include groundwater or surface water elevations, low-flow groundwater sampling, well development, hydraulic testing, and soil physical properties. There are also data resources within the public domain that are used for many hydrogeologic-based purposes, such as barometric pressure, precipitation, and stream flow. These data sources are documented in separate reports and archived by different agencies or companies. Ingesting or transforming the data sets into accessible formats is challenging; however, desktop tools are now available to help realize the benefits of consolidating these big data sets into a unified, user-friendly platform. Examples of hydrogeologic-based data sets include:

- Groundwater and surface water elevations.
  - Manual gauging data that are periodically collected during routine groundwater sampling events may span many years. Often these data are collected monthly to annually with the most valuable data collected more frequently (monthly to quarterly) allowing practitioners to observe temporal (e.g., seasonal) effects.
  - High-resolution water elevation data in time-series often collected by pressure transducers provides valuable insights into the dynamic nature of hydrologic systems. Although high-resolution data may be constrained to specific events such as hydraulic testing periods, obtaining longer-term data sets (months to years) can accurately identify the effects of stresses on groundwater systems (Alley and Taylor 2001) adding further characterization value. For example, by comparing time-series data across multiple georeferenced monitoring points of the same network, we can gain improved understanding of the interconnectedness of complex groundwater systems, evaluate groundwater = surface water interactions, discern changes in groundwater flow patterns, or assess horizontal and vertical groundwater flux.
- Low-flow groundwater sampling.

  Sampling data are also collected routinely. Valuable data include those obtained by low-flow methodologies that consist of low stress, constant flow rates, and steady drawdown that can be used to calculate hydraulic conductivity estimates (Robbins et al. 2009; Aragon-Jose and Robbins 2011). These data, along with groundwater quality parameters, can also be used to identify changes in well performance that may be related to seasonal saturated thickness changes or declines in well efficiencies due to fouling that may be improved through well redevelopment.
- Well development.

  Data collected during initial and re-development activity, when properly executed, can be used to further refine performance criteria such as specific capacity, estimates of hydraulic conductivity, yield, and water quality. These data can be used to assess well conditions and performance over time.
- Hydraulic testing.

  Many different types of hydraulic testing are completed for compliance, design, or modeling. The results of the testing are usually only shown as calculated output values that support evaluations or modeling and are presented without the raw data. Not only are the interpreted measurements valuable for quality review and analysis verification, but the response time-series can be used for several evaluation purposes such as supplemental characterization of boundary conditions or hydraulic capture analysis and mass loading/mass flux, when combined with groundwater sampling.
- Soil physical properties.

  Many site investigations involve subsurface drilling and soil core collection within unconsolidated formations. Target lithologic intervals are sampled to determine particle size distributions (PSD) and the data are then used for relative permeability estimates. This extends the data value by better supporting evaluations with tools such as hydrostratigraphic flux-based frameworks and fate and transport models.

There are other example data sets that are not as common as the ones above. However, once any data set is gathered from existing information, or part of current/future data collection planning, the data treatment will require organization and adherence to standards and procedures, that is, they need to be consistent and use the right tools to store and access information with logical workflows in a continuous lifecycle that extends from existing data to new data, analysis/processing, and reporting. Using a standardized framework improves data quality by organizing and mapping the data as they are collected.

Unlocking valuable data trapped in old paper records, electronic scans of reports and forms, or legacy spreadsheets, is essential to derive the most meaningful insights. These data sets may encompass decades of information and require the use of techniques such as optical character recognition or utilizing developed data ingestion protocols from electronic files which can help streamline processes and overcome inefficiencies. Despite the clear benefits of digital transformation practices, some practitioners remain complacent, adhering exclusively to traditional paper-based data recording and storage methods. While paper-based data collection may still be required or desirable in some circumstances, the availability of data translation tools and AI dictation tools can facilitate the transition to digital formats. The practitioner community is improving with data reporting practices that now offer stakeholders access to data interfaces and packaged data, enhancing collaboration and transparency. Standardizing pre-existing data formats and using digital means for on-going data collection, will further improve efficiency and workflows.

Advancing Data Analytics in Hydrogeology

New tools have been developed that use best practices for data management. Not only do these platforms effectively disseminate data, they support efficient workflow by allowing better control of field instrumentation (e.g., monitoring of battery life and memory availability, assessment of drift and data signal quality, and remote designation of data collection parameters). These tools also facilitate data connections between sources, easing advanced data transformations, or analytics to enable efficient and automated methods that lead to valuable insights and knowledge. This approach *reduces* the effort, *repurposes* data, and *reimagines* the process. Several examples of developed tools and novel technologies currently in use that demonstrate the integration of hydrogeologic data, while ensuring quality and proper treatment based on the data type, are presented in the following sections.

Water Level Processing Tool

While high-resolution (here defined to be data collection frequencies greater than 1 per hour) water level monitoring has become more prevalent with technological advances and decreasing equipment costs (Horst et al. 2022), the difficulties of accessing, viewing, and processing these increasingly large data sets often yield diminishing returns and demands considerable time. As these data sets continue to increase in size (and resolution), automated tools are needed to reduce processing time and correct water level data so that it can be viewed and utilized in real time. For high-resolution groundwater level data, processing is more complex compared to surface water and includes barometric pressure compensation if absolute instruments are used, elevation calibration from a survey point, and even barometric or tidal correction, if required (Rasmussen and Crawford 1997; Gonthier 2007; Butler Jr et al. 2011; Fileccia 2011).

Multiple software packages or cloud services are used to communicate with or download pressure transducer data and adjust/compensate for site or well-specific parameters. However, these packages are typically not agnostic or universally compatible, potentially impeding efforts to interface and process the various data sets. The Water Level Processing Tool (WLPT), which is a high-resolution web-based digital twin engine, is an example tool that addresses the need for a "one-stop-shop" approach to ingest, process, correct, and remove fluctuations when needed from groundwater level data sets (Fortner III and Hollister 2022) (Figure 1). The tool utilizes automated ingestion, a common data platform for storage, and coded transformation for data and quality control procedures. Commercially available pressure transducers and sensors are compatible with the cloud or automated email ingestion process and the tool is scalable for small to big data sites. In addition, pre-loading of metadata that include well details (e.g., well construction), survey information, and pressure transducer device specifics into reference tables are used in the field as pick lists in a mobile app for

Transducer By Well: MW-A (#SN), MW-B (#SN), MW-C (#SN)

Time Range: 2024-02-01 13:07 - 2024-03-31 13:07

Figure 1. Water Level Processing Tool example data set showing post calibration data, change in water level over time, and temperature.

data capture when remote telemetry is not available. As mentioned above, pre-existing water level data that have been, or still require, processing can also be integrated. The resulting interactive WLPT features graphical and map views, quality control protocols, data metrics, and finalized results. It enables seamless access to processed and calibrated water elevation data, which can be exported for tabulation, additional visualizations, or reporting for compliance purposes.

The final processed water level data provides a foundation for reimagining the data in the future. Examples include:

1. Transforming data to drawdown data sets for specified hydraulic testing periods, or the assessment of data quality for use in modeling exercises.
2. Analysis of groundwater level influence by barometric pressure or ocean/earth tides that can be used to estimate formation porosity, level of confinement, transmissivity, or specific storage (Bailey 2017; Fuentes-Arreazola et al. 2018; McMillan et al. 2019).
3. Groundwater—surface water interaction studies that correlate fluctuation responses and relative water level elevations.
4. Temporal hydraulic gradient analysis to evaluate horizontal and/or vertical groundwater flow.

Advanced Analytics Example Application

An example of the advanced analytics now possible in groundwater studies is presented under the Horizontal Hydraulic Gradient Calculator (HHGC). This tool is an efficient way to repurpose results from the WLPT and use the data for determining the direction and magnitude of groundwater flow from groundwater elevation time-series data utilizing triplet wells sets. Online tools are available for calculating gradients from two locations or using monitoring well triplets (e.g., USEPA 2021), although they are limited, particularly in the number of well sets that can be computed simultaneously. While macro-enabled Excel spreadsheet tools (e.g., 3PE and HydrogeoEstimatorXL) increase the number of well triplets analyzed at one time, they also have data limitations (Beljin et al. 2014; Devlin and Schillig 2017). The data processing code that has been developed for the HHGC reimagines, via seamless integration, the WLPTs data analysis by continuously running gradient calculations on well triplets with big data sets. There are multiple advantages in calculating high time-resolution gradients rather than limiting the collection and analysis to a quarterly or annual period, as gradient direction and magnitude may vary substantially in response to precipitation, drought, or surface water influence (Fortner III et al. 2024). Evaluating transient gradient changes can also inform remedy designs to accommodate variations in groundwater levels and flow direction and associated potential influences on contaminant mass distribution, injected reagent transport, and remediation performance.

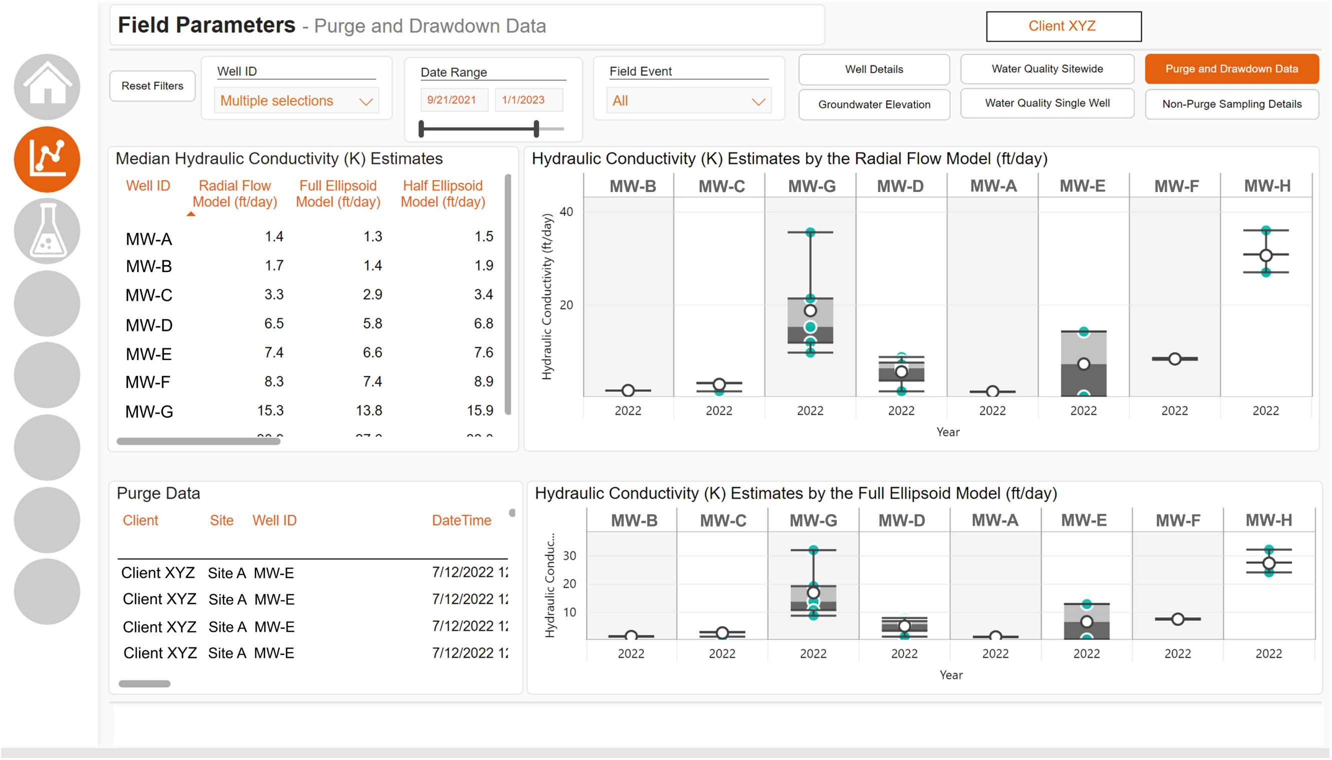
Low-Flow Drawdown Tool

Hydraulic conductivity is a fundamental hydrogeologic parameter essential for the characterization and development of CSMs to support a multitude of analyses such as flux within hydrostratigraphic units or groundwater flow modeling. Slug tests and/or pumping tests are traditional in-well or drill stem test methods used to estimate hydraulic conductivity in aquifers. However, logistical or physical limitations may be present that prevent or constrain the performance of these tests (e.g., due to restrictions on accessibility, generated waste volumes, or budget). Commonly available water level data (drawdown) from low-flow groundwater sampling may be repurposed to estimate hydraulic conductivity using reliable steady-state discharge and drawdown results (Robbins et al. 2009; Aragon-Jose and Robbins 2011). The calculation uses simplistic analytical solutions that were nonetheless found to be comparable to slug testing with a calculated upper hydraulic conductivity limit in the range of approximately 10^{-3} to 10^{-2} cm/s and may be applicable to values as low as 10^{-6} cm/s (Robbins et al. 2009). While maximum discharge rates of 1 L/min may be required by regulatory guidance (USEPA 2017), the flow rate may be increased to as much as 4 L/min in highly conductive groundwater zones, as long as the flow rate does not induce an appreciable drawdown response of greater than approximately 0.2 ft (Fortner III et al. 2013).

Automation of the calculations with an Excel-based tool was developed based on the solutions presented by Robbins et al. (2009) (Negrao 2021). However, the tool was not optimally configured to address very large data sets. By leveraging low-flow field digital data with available databases, the use of the data was reimagined to combine the discharge measurements that meet steady-state criteria and apply an automated hydraulic conductivity calculation with a Low-Flow Drawdown Tool (LFDT). Pre-loaded monitoring well metadata provides the physical requirements to calculate hydraulic conductivity estimates from all three analytical solutions presented in Robbins et al. (2009). A dashboard view facilitates the database connections and allows the user to evaluate multiple results at individual wells or many wells (Figure 2). The repurposing of these widely available data further informs the understanding of the site permeability distribution and reduces labor costs by automating hydraulic testing data reduction. Additional transformations provide differential views from event to event to identify outliers arising from data quality problems and to identify potential well performance issues (i.e., decreasing hydraulic conductivity may indicate required well redevelopment).

Sieve to Hydraulic Conductivity (K) Tool

PSD data can be used to develop hydraulic conductivity (K) estimates within granular formations. An automated Sieve to K Tool (SKT) was developed based on the Excel-based program HydrogeoSieveXL (Devlin 2015) to streamline the calculation of K estimates utilizing PSD data (Spurlin et al. 2024). The value of the conventional spreadsheet method is well-established with environmental practitioners as a beneficial starting point. The primary objectives of the SKT were to refine data ingestion, reduce the time required for data processing and evaluation, repurpose the PSD data, and reimagine the use of conventional methods by applying them to big data. The SKT extends the concept that includes 16 established calculation methods already included in HydrogeoSieveXL to provide a comprehensive indication of the statistically supported range of K that can be applied



Median Hydraulic Conductivity (K) Estimates

Well ID	Radial Flow Model (ft/day)	Full Ellipsoid Model (ft/day)	Half Ellipsoid Model (ft/day)
MW-A	1.4	1.3	1.5
MW-B	1.7	1.4	1.9
MW-C	3.3	2.9	3.4
MW-D	6.5	5.8	6.8
MW-E	7.4	6.6	7.6
MW-F	8.3	7.4	8.9
MW-G	15.3	13.8	15.9

Purge Data

Client	Site	Well ID	DateTime
Client XYZ	Site A	MW-E	7/12/2022 1
Client XYZ	Site A	MW-E	7/12/2022 1
Client XYZ	Site A	MW-E	7/12/2022 1
Client XYZ	Site A	MW-E	7/12/2022 1

Figure 2. Low-Flow Drawdown Tool dashboard example showing hydraulic conductivity estimates for multiple wells over several sampling events.

to many data sets. A digital workflow integrates laboratory electronic data deliverables (EDDs) of PSD results with automated data quality review, formatting, analyses, and reporting. The SKT integrates the same fundamental applications built into the conventional HydrogeoSeiveXL tool through logic scripts and developed code to calculate effective particle size diameters. An innovative feature includes extrapolation to the zero (fine-grained) fraction using monotone piecewise cubic interpolation that is further computed with a decision matrix for when the extrapolation should be applied. Qualitative descriptions of the soil samples are also provided along with calculated weight percentages (in standard sieve and hydrometer ranges).

Estimates of K are subsequently calculated using each of the established methods require the practitioner's judgment to determine that criteria are met for method validity of the results according to underlying assumptions. The resulting K estimates are reported for each method (in preferred units) and arithmetic and geometric means are calculated with an automated recommendation for selecting a representative mean as an expression of the central tendency. As a final step, the SKT generates a summary of the PSD evaluation for each individual sample and a master summary table of all outputs as a batch export (Figure 3).

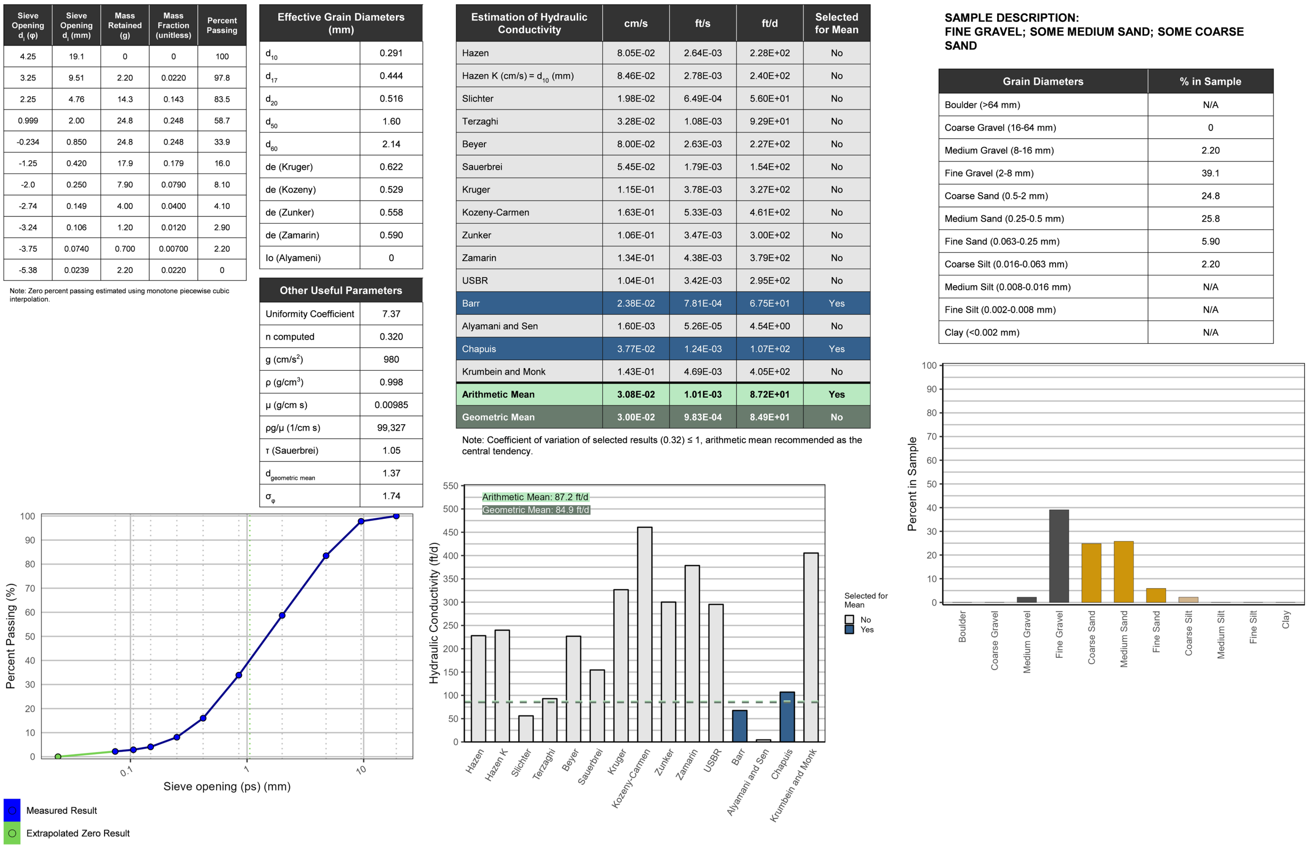
The new automated tool expedites the data analysis and visualization process for an established industry standard approach to PSD. The tool eliminates traditional manual data entry, has the capability to analyze an unlimited number of particle size results as batch exports, incorporates strengthened statistical review, auto-generates report-ready exhibits, and greatly reduces the overall data processing time required by the conventional spreadsheet process, resulting in a 600% improvement to productivity (irrespective of project scale) and significant associated cost savings.

AiSieve

One of the main challenges of obtaining PSD data from unconsolidated soils or materials is that it is not easily quantified in the field. Soil samples must be collected and then subjected to physical sieving methods, most often at an off-site fixed laboratory setting. Therefore, the current practice typically involves visual qualitative description of soil core samples by a field geologist, with only a small subset of samples submitted for quantitative PSD analyses (usually to minimize shipping and laboratory costs). The result is a disconnect between field assessment and laboratory analyses, leading to a delay of several weeks until the field and laboratory data can be synthesized and used to progress project characterization.

A new application, AiSieve, (under development by AiTera in collaboration with the corresponding author) uses AI-powered image analysis to generate quantitative PSDs from soil sample images. The current image acquisition system is a portable device designed for capturing soil sample images with a compact AmScope 18 megapixel camera (Figure 4). The images are transmitted to AiSieve, an advanced image processing system that uses AI neural net algorithms to generate highly resolved PSD data and soil type classification.

AiTera has trained and improved particle size recognition by embedding IBM Maximo Visual Inspection (MVI) software to enlarge the reference data set and improve



Sieve Opening d_i (φ)	Sieve Opening d_i (mm)	Mass Retained (g)	Mass Fraction (unitless)	Percent Passing
4.25	19.1	0	0	100
3.25	9.51	2.20	0.0220	97.8
2.25	4.76	14.3	0.143	83.5
0.999	2.00	24.8	0.248	58.7
-0.234	0.850	24.8	0.248	33.9
-1.25	0.420	17.9	0.179	16.0
-2.0	0.250	7.90	0.0790	8.10
-2.74	0.149	4.00	0.0400	4.10
-3.24	0.106	1.20	0.0120	2.90
-3.75	0.0740	0.700	0.00700	2.20
-5.38	0.0239	2.20	0.0220	0

Note: Zero percent passing estimated using monotone piecewise cubic interpolation.

Effective Grain Diameters (mm)	
d_{10}	0.291
d_{17}	0.444
d_{20}	0.516
d_{50}	1.60
d_{60}	2.14
de (Kruger)	0.622
de (Kozeny)	0.529
de (Zunker)	0.558
de (Zamarin)	0.590
Io (Alyameni)	0

Other Useful Parameters	
Uniformity Coefficient	7.37
n computed	0.320
g (cm/s^2)	980
ρ (g/cm^3)	0.998
μ (g/cm s)	0.00985
ρg/μ (1/cm s)	99,327
τ (Sauerbrei)	1.05
$d_{geometric\ mean}$	1.37
σ_{φ}	1.74

Estimation of Hydraulic Conductivity	cm/s	ft/s	ft/d	Selected for Mean
Hazen	8.05E-02	2.64E-03	2.28E+02	No
Hazen K (cm/s) = d_{10} (mm)	8.46E-02	2.78E-03	2.40E+02	No
Slichter	1.98E-02	6.49E-04	5.60E+01	No
Terzaghi	3.28E-02	1.08E-03	9.29E+01	No
Beyer	8.00E-02	2.63E-03	2.27E+02	No
Sauerbrei	5.45E-02	1.79E-03	1.54E+02	No
Kruger	1.15E-01	3.78E-03	3.27E+02	No
Kozeny-Carmen	1.63E-01	5.33E-03	4.61E+02	No
Zunker	1.06E-01	3.47E-03	3.00E+02	No
Zamarin	1.34E-01	4.38E-03	3.79E+02	No
USBR	1.04E-01	3.42E-03	2.95E+02	No
Barr	2.38E-02	7.81E-04	6.75E+01	Yes
Alyamani and Sen	1.60E-03	5.26E-05	4.54E+00	No
Chapuis	3.77E-02	1.24E-03	1.07E+02	Yes
Krumbein and Monk	1.43E-01	4.69E-03	4.05E+02	No
Arithmetic Mean	**3.08E-02**	**1.01E-03**	**8.72E+01**	**Yes**
Geometric Mean	**3.00E-02**	**9.83E-04**	**8.49E+01**	**No**

Note: Coefficient of variation of selected results (0.32) ≤ 1, arithmetic mean recommended as the central tendency.

SAMPLE DESCRIPTION:
FINE GRAVEL; SOME MEDIUM SAND; SOME COARSE SAND

Grain Diameters	% in Sample
Boulder (>64 mm)	N/A
Coarse Gravel (16-64 mm)	0
Medium Gravel (8-16 mm)	2.20
Fine Gravel (2-8 mm)	39.1
Coarse Sand (0.5-2 mm)	24.8
Medium Sand (0.25-0.5 mm)	25.8
Fine Sand (0.063-0.25 mm)	5.90
Coarse Silt (0.016-0.063 mm)	2.20
Medium Silt (0.008-0.016 mm)	N/A
Fine Silt (0.002-0.008 mm)	N/A
Clay (<0.002 mm)	N/A

Figure 3. Automated Sieve to K Tool summary export of the particle size distribution evaluation for an individual sample.

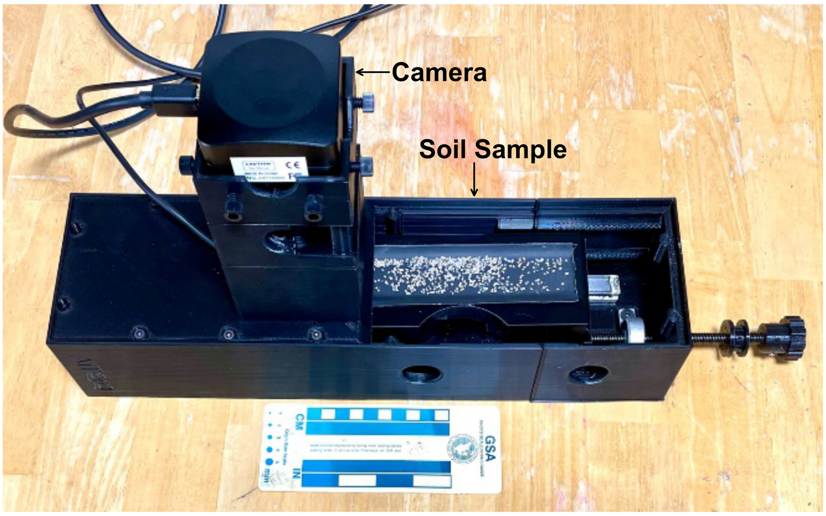


Figure 4. Current AiSieve image acquisition system prototype.

performance for PSD recognition. A unique algorithm was developed using You Only Look Once (YOLO) open software and improved precision comparing results to the ground truth provided by laboratory analysis with more than 20 natural sandy soil types. AiSieve currently processes samples in less than 10 s, enabling the non-destructive analysis of hundreds of samples daily, providing real-time PSD information to field geologists. These immediately available data can support field decisions (e.g., soil classification, sample collection, well design) and provide repeatable quantitative information, eliminating human-based variations of soil type classifications. The data can also be shared with stakeholders who need this information for immediate action or simple consultation.

AiSieve also automatically generates a report that includes PSD results, representative grain sizes (e.g., d10, d50), and hydraulic conductivity estimates using multiple methods and can be incorporated with the SKT (e.g.,

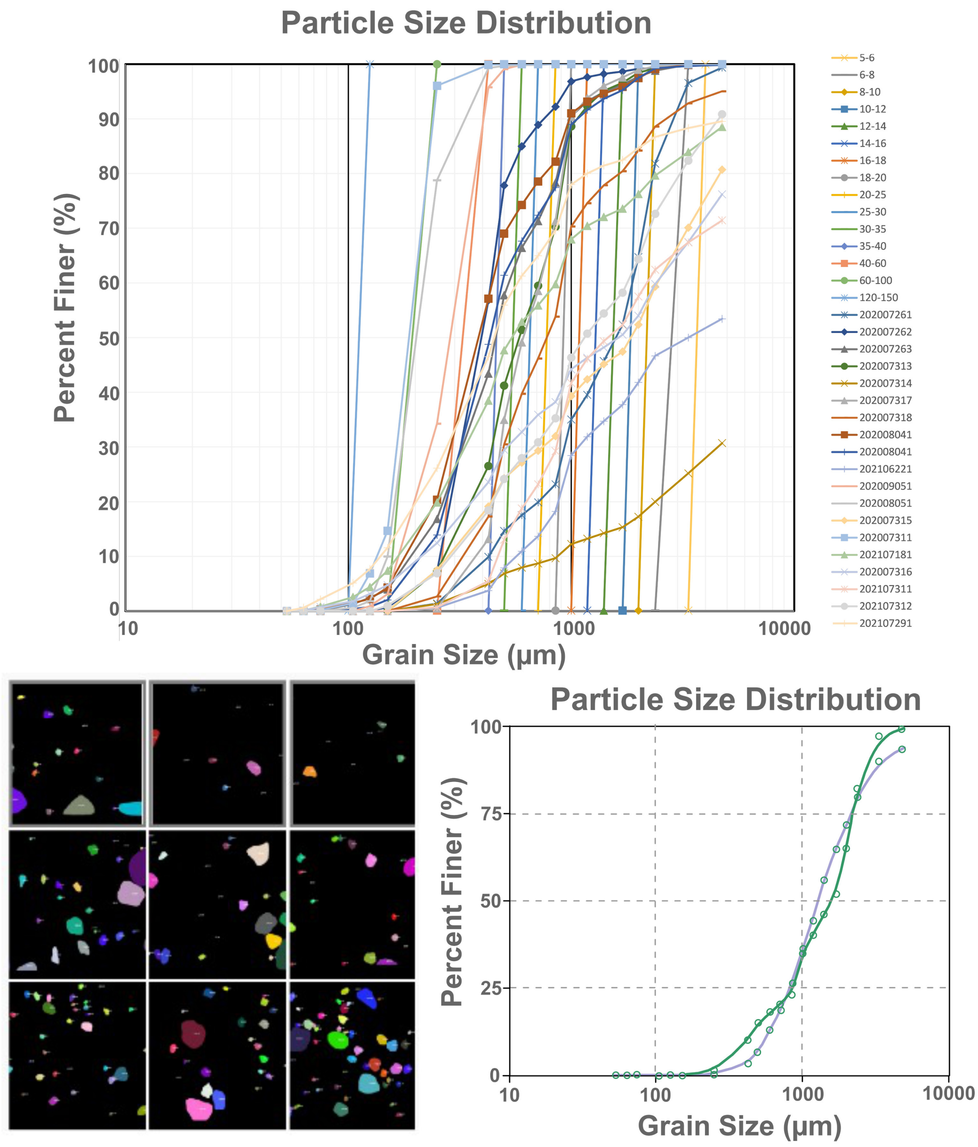


Figure 5. Top: Soil PSD library used to train AiSieve. Bottom Left: individual soil grains identified and quantified by AiSieve. Bottom Right: Example AiSieve results (blue series) compared to measured PSD data (green series). Courtesy Daniel Fortin.

Devlin 2015, Figure 5). These reports are readily customizable (units, formatting, etc.) and increase workflow efficiency, streamlining data processing for visualization and modeling. When scaled up across multi-year projects and a portfolio of project sites, the technology is anticipated to translate into significant cost savings for applicable project sites. The PSDs generated by AiSieve provide key standalone material characterization and can also feed into additional analyses, including the following:

- Estimates of hydraulic conductivity using previously established empirical relationships and based on a framework presented by Devlin (2015) and using the SKT presented above that streamlines many analyses. Refined estimates of hydraulic conductivity on a horizontal and vertical scale achieved using AiSieve can support refined site characterization including groundwater flow models.
- High-resolution lithologic characterization, which can support stability assessments, geotechnical analyses, and water fate and transport evaluations (e.g., flow direction and rate, low/no flow zones, hydraulic residence time).
- Estimates of sphericity and roundness (capability to be developed) to assess the relationship of the grain shape factor to porosity and permeability, which play a role in associated geochemical reactions.
- Material saturation assessment (i.e., vadose zone, variably saturated zone, saturated zone) to assess geochemical conditions, reaction potentials, and solute transport.
- High-resolution bulk material characterization to support reclamation and revegetation assessments.

AiSieve is anticipated to be commercially available by the end of 2024 and is expected to offer several improvements over current processes and practices, as well as the potential for much broader environmental and geotechnical applications such as water resource development, coastal stability analysis and modeling, wildfire recovery and erosion mitigation, and geotechnical engineering.

Reduce, Repurpose, Reimagine

As data collection methods improve, hydrogeologic-focused data sets are only going to continue to increase in volume and resolution. As demonstrated by the examples above, reimagining how to process, manage, and evaluate these data need not stem from novel methodologies or sophisticated coding, but can instead grow from building or repurposing existing approaches and reducing processing efforts with efficient workflows and automation designed to interface with big data. Ultimately, the goals of the presented ideas and associated developed tools are to centralize big data, improve efficiency, and minimize efforts, thereby freeing up more time for practitioners to focus on the data meaning and implications.

Historically, CSMs have been relatively data poor and limited by insufficient data, particularly related to water levels, despite advancements in high-resolution site characterization (HRSC). The advances in HRSC has not been matched by similar progress in effectively managing the different types of data used for site characterization. By unlocking these data sets, the door is opened to a more expansive picture of our hydrogeologic systems. For example, while the HydrogeoEstimatorXL tool can be used for calculating horizontal hydraulic gradients, those results can also be combined with hydraulic conductivity and contaminant mass to evaluate groundwater and mass flux (Devlin and Schillig 2017). Reimaging the groundwater or contaminant mass flux using transient gradients (e.g. HHGC) expands the knowledge of changing conditions based on natural variation or induced remediation variation of stresses. Future developments will include advanced analytical modules and trend removal options that tie to the WLPT to repurpose the high-resolution water level data for various objectives. Repurposing the results from SKT to support remediation well design calculations (i.e., filter pack and screen slot size specifications) is an example of design module integration. Advanced analytics will also be used to define remediation system design criteria.

The use of AI capability to enable quality control will further improve how we interact with data (Horst et al. 2022); AI training with tacit knowledge and AI-powered predictions is on the horizon. Reimagined in-field tools include using real-time, quantification technology for PSD and/or development of advanced direct push tools integrated with AI analysis, such as AiSieve, to enhance in-situ hydraulic data collection.

The integration of these new tools into broader hydrogeological assessments will enable reimagining the understanding of groundwater dynamics and contaminant transport. Advanced analytics, AI, and real-time technologies are keys that will unlock new insights and enhancing decision-making processes in the realm of hydraulic data analysis. The "reduce, repurpose, and reimagine" approach to these data sets is a useful framework to optimally process, manage, and evaluate hydrogeologic data.

Supporting Information

Additional Supporting Information may be found in the online version of this article. Supporting Information is generally not peer reviewed.

Audio S1. Summary of the main features of this article.

References

Alley, W.M., and C.J. Taylor. 2001. The value of long-term ground water level monitoring. *Groundwater* 39, no. 6: 801–802.

Aragon-Jose, A.T., and G.A. Robbins. 2011. Low-flow hydraulic conductivity tests at wells that cross the water table. *Groundwater* 49, no. 3: 426–431. https://doi.org/10.1111/j.1745-6584.2010.00742

Bailey, B. 2017. Assessing the utility of barometric response functions in estimating hydrogeological parameters of the High Plains Aquifer. Doctoral dissertation, University of Kansas.

Beljin, M., R. Ross, and S. Acree. 2014. 3PE: A tool for estimating groundwater flow vectors. U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-14/273.

Butler, J.J. Jr., W. Jin, G.A. Mohammed, and E.C. Reboulet. 2011. New insights from well responses to fluctuations in barometric pressure. *Groundwater* 49, no. 4: 525–533. https://doi.org/10.1111/j.1745-6584.2010.00768

Devlin, J.F. 2015. HydrogeoSieveXL: An excel-based tool to estimate hydraulic conductivity from grain-size analysis. *Hydrogeology Journal* 23, no. 4: 837–844. https://doi.org/10.1007/s10040-015-1255-0

Devlin, J.F., and P.C. Schillig. 2017. HydrogeoEstimatorXL: An excel-based tool for estimating hydraulic gradient magnitude and direction. *Technical Note in the Hydrogeology Journal* 25: 867–875. https://doi.org/10.1007/s10040-016-1518-4

Fileccia, A. 2011. Correcting water level data for barometric pressure fluctuations: theoretical approach and a case history for an unconfined karst aquifer (Otavi, Namibia). *Acque Sotterranne* 126: 23–44.

Fortner, E.H. III, C.O. Barton, W. Patterson, and M.W. Killingstad. 2024. A step in the right direction: Untangling groundwater dynamics in the face of climate change. Poster Presented at Battelle Thirteenth International Conference on Remediation of Chlorinated and Recalcitrant Compounds in Denver, Colorado. June 3.

Fortner, E.H. III, and C. Hollister. 2022. Making waves in high-resolution water-level data for decision insights. National Groundwater Association, Groundwater Week 2022.

Fortner, E.H. III, M.W. Killingstad, and J. Quinnan. 2013. Low stress pumping tests to evaluate mass flux in a highly permeable aquifer. Presented at NGWA Summit – The National and International Conference on Groundwater in San Antonio, TX. April 29.

Fuentes-Arreazola, M.A., J. Ramírez-Hernández, and R. Vázquez-González. 2018. Hydrogeological properties estimation from groundwater level natural fluctuations analysis as a low-cost tool for the Mexicali Valley aquifer. *Water* 10, no. 5: 586. https://doi.org/10.3390/w10050586

Gonthier, G.J. 2007. A Graphical Method for Estimation of Barometric Efficiency from Continuous Data – Concepts and Application to a Site in the Piedmont, Air Force Plant 6, Marietta, Georgia. U.S. Geological Survey Scientific Investigations Report 2007-5111, 29 p. http://pubs.usgs.gov/sir/2007/5111/ (accessed June 1, 2024).

Horst, J., N. Welty, J. Gallegos, D. Dunham, and A. Adams. 2022. The rapid advancement of environmental sensors in remediation. *Ground Water Monitoring and Remediation* 42, no. 2: 12–19. https://doi.org/10.1111/gwmr.12516

McMillan, T.C., G.C. Rau, W.A. Timms, and M.S. Andersen. 2019. Utilizing the impact of earth and atmospheric tides on groundwater systems: A review reveals the future potential. *Reviews of Geophysics* 57, no. 2: 281–315. https://doi.org/10.1029/2018RG000630

Negrao, P. 2021. Excel spreadsheet to determine hydraulic conductivity from low flow sampling field data. Presented at the International Conference on Contaminated Land Management and Rehabilitation, Lisbon. May 11–14.

Payne, F.C., J.A. Quinnan, and S.T. Potter. 2008. *Remediation Hydraulics*, 1st ed. Boca Raton: CRC Press. https://doi.org/10.1201/9781420006841

Rasmussen, T.C., and L.A. Crawford. 1997. Identifying and removing barometric pressure effects in confined and unconfined aquifers. *Groundwater* 35, no. 3: 502–511. https://doi.org/10.1111/j.1745-6584.1997.tb00111

Robbins, G.A., A.T. Aragon-Jose, and A. Romero. 2009. Determining hydraulic conductivity using pumping data from low-flow sampling. *Groundwater* 47, no. 2: 271–286. https://doi.org/10.1111/j.1745-6584.2008.00519

Spurlin, M.S., C. Cisco, and D. Profusek. 2024. A new automated approach to grain size analysis for environmental practitioners. Presented at the Battelle Chlorinated Conference, Denver, Co. June 5.

United States Environmental Protection Agency (USEPA). 2021. EPA on-line tools for site assessment calculation. Hydraulic Gradient, three-point gradient calculator. https://www3.epa.gov/ceampubl/learn2model/part-two/onsite/gradient3.html (accessed June 1, 2024).

United States Environmental Protection Agency (USEPA), Region 1. 2017. Low stress (low flow) purging and sampling procedure for the collection of ground water samples from monitoring wells. SOP #: G0001, Revision 4, Sept. 19. North Chelmsford, Massachusetts.

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