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TECHNICAL ARTICLE

Coupled Baseline Estimation and Trend Analysis Approach to Differentiate Natural and Mine-Related Stresses on Groundwater Levels

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Abstract

Permitting and regulatory obligations require mine operators to periodically report the spatial extent of mine-induced water-level changes, and to provide water-level monitoring data for review, along with explanations of all hydrologic stresses causing water-level trends. This study couples a baseline-estimation method with a curve-fitting trend-analysis approach to determine all natural, mining, and non-mining aquifer stresses affecting water levels in wells. The approach was applied to the Twin Creeks Mine monitoring network in north-central Nevada, USA. Stresses identified in wells were used to delineate the approximate extent of pumping effects and indicated that drawdowns had not coalesced between mining and non-mining pumping areas. Trend-analysis results indicated that 10 study-area well hydrographs have natural trends, and statistical methods identified three of these wells as having statistically significant downward trends. Thus, caution should be used when interpreting the meaning of statistically significant downward trends, because the downward trend may be climate driven rather than pumping related. The curve-matching approach requires the development of a baseline water-level trend to understand expected natural fluctuations. The baseline trend assumes a dynamic-equilibrium natural condition, where long-term net changes in groundwater levels are zero. The baseline trend and trend analysis require a recharge proxy for the study area. This study developed recharge proxies using winter precipitation data, peak reservoir-storage volumes, and metered mine-water discharge to a surface-water channel. The curve-matching approach also can be used to identify and remove erroneous data, reconcile water-level and pumping datasets, or build hydrologic conceptualizations.

Keywords Aquifer stresses · Recharge proxy · Predevelopment water level · Statistical trend analysis

Introduction

Mining operations can affect the groundwater system. Groundwater levels decline in response to active and passive dewatering (Henton 1981; Timms et al. 2018). Conversely, groundwater levels rise in response to pumping-recovery (Henton 1981; Timms et al. 2018); mine-induced infiltration at rapid infiltration basins (Davis et al. 2022; Nimmer et al. 2009); and stream infiltration following mine-water discharge to streams or unlined ditches.

Mine operators are required to understand the spatial extent of mine-induced water-level declines and rises for permitting and regulatory purposes. Because mining and non-mining (e.g. agricultural) water users can affect community water supplies or groundwater-dependent ecosystems, mine operators also need to understand where their mining operations are not affecting the groundwater system.

Water-level monitoring networks are used to understand historic and current effects of mine-related pumping and infiltration on the groundwater system. At wells adjacent to mining facilities, large water-level rises and declines can be readily attributed to mining activities. However, farther from the mine site, mine-related pumping and infiltration stresses are attenuated by hydraulic properties of the groundwater system and these stresses can be masked by natural water-level trends.

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Understanding natural trends is important because groundwater levels can rise and decline naturally in response to precipitation-derived recharge and groundwater discharge to streams, springs, and phreatophyte areas. An observed water-level decline can result from natural or pumping stresses. Differentiating the source of the decline is more difficult when water-level declines are small, because correct attribution of the decline is based on an understanding of long-term, natural, water-level trends in the groundwater system and the likely distant propagation of drawdown from the pumping center.

Once the long-term natural trend is understood, then a water-level trend analysis can be done to attribute all natural and anthropogenic stresses affecting water levels in wells within a monitoring network. Typical water-level trend analysis methods use statistical-based nonparametric approaches (Helsel et al. 2020), such as the Kendall-Theil robust line method (Fenelon 2000), Mann–Kendall test (Hamed and Rao 1998; Kumar et al. 1998; Kumar and Rathnam 2019; Lou et al. 2019; Minea et al. 2022; Ribeiro et al. 2015; Sinha 2023; Vinushree et al. 2022; Yue et al. 2002;), Sen's Slope (Kumar et al. 1998; Minea et al. 2022; Ribeiro et al. 2015; Sinha 2023; Vinushree et al. 2022), or Spearman's Rho test (Minea et al. 2022; Yue et al. 2002). However, these statistical approaches are constrained by sample size and only quantify significant upward or downward monotonic trends. Multivariate statistical approaches, such as principal-component analysis (Jung et al. 2021; Winter et al. 2000), have been used to quantify variables affecting water-level trends; however, results of these type of analyses are not always intuitive when presented to regulators.

The three objectives of this study are to: (1) present a method for estimating a baseline water-level trend that represents long-term natural water-level fluctuations in the groundwater system prior to mine operations; (2) present a curve-matching trend analysis approach to determine all natural, mining, and non-mining stresses affecting water levels in wells; and (3) use trend-analysis results to delineate the approximate extent of mining and non-mining effects on a groundwater system. The water-level monitoring network at the Twin Creeks (TC) Mine in north-central Nevada, USA, is used as a case-study example for the trend analysis and baseline water-level estimation.

Site Description

The TC Mine is about 55 km northeast of Winnemucca, in north-central Nevada. Active mine features at the TC Mine include North Mega, South Mega, and Vista Pits, and an underground mine beneath Vista Pit (Fig. 1). The TC Mine monitoring network includes well sites that are measured quarterly or semi-annually; these data are reported annually to the Nevada Division of Water Resources. The wells are in two surface-water hydrographic areas (HAs): Kelly Creek Valley and Little Humboldt Valley (Fig. 1).

Note that Turquoise Ridge (TR) Mine is about 8 km southwest of TC Mine but was excluded in this study for a few reasons. First, TR Mine is operated entirely by passive dewatering from low-transmissivity bedrock. Second, passive dewatering has resulted in small (less than 15 m) water-level declines that are localized to the footprint of the mine site. Lastly, wells selected for this scope of work were vetted through extensive analysis to ensure that water-level trends have not been impacted by passive dewatering from TR Mine.

The TC Mine is within the Basin and Range Province (Harrill and Prudic 1998), which is characterized by extensional tectonic forces that cause down-dropped fault blocks to form valleys and upthrown fault blocks to form intervening mountain ranges. The TC Mine is on Kelly Creek valley floor, which is bounded on the west and east by the Osgood and Snowstorm Mountains, respectively (Fig. 1). Land-surface altitudes range from 1310 to 1520 m above mean sea level (amsl) on the Kelly Creek valley floor. Land-surface altitudes are up to 2645 m amsl in the Osgood Mountains and up to 2561 m amsl in the Snowstorm Mountains.

Climate

The study-area climate is a semi-arid steppe, with hot summers and cold winters. The climate is characterized by low relative humidity, low annual precipitation, and high potential evapotranspiration. Average maximum temperatures range from 14 to 26 °C in summer, and from −12 to 6 °C in winter (NOAA 2023a). Average annual precipitation ranges from 0.6 m in the Osgood and Snowstorm Mountains to 0.2 m on the Kelly Creek valley floor (Climate Engine 2023). Average annual pan and open-water evaporation rates are 1.7 and 1.2 m, respectively (Itasca 2022).

Hydrogeology

Quaternary alluvium and Paleozoic fractured rocks form the primary aquifers in the study area, and Tertiary volcanics form a secondary fractured-rock aquifer (Itasca 2022). Quaternary alluvium composes unconsolidated sediments that occur on the valley floors, along surface-water channels, and in alluvial fans (Fig. 1). The alluvial aquifer is recharged mostly by surface-water flows along losing reaches of Jake Creek, Kelly Creek, Rabbit Creek, and the Humboldt River. Undifferentiated Paleozoic rocks underlie much of the study area and consist of fractured carbonate and siliciclastic rocks, predominantly limestone, chert, greenstone, quartzite,

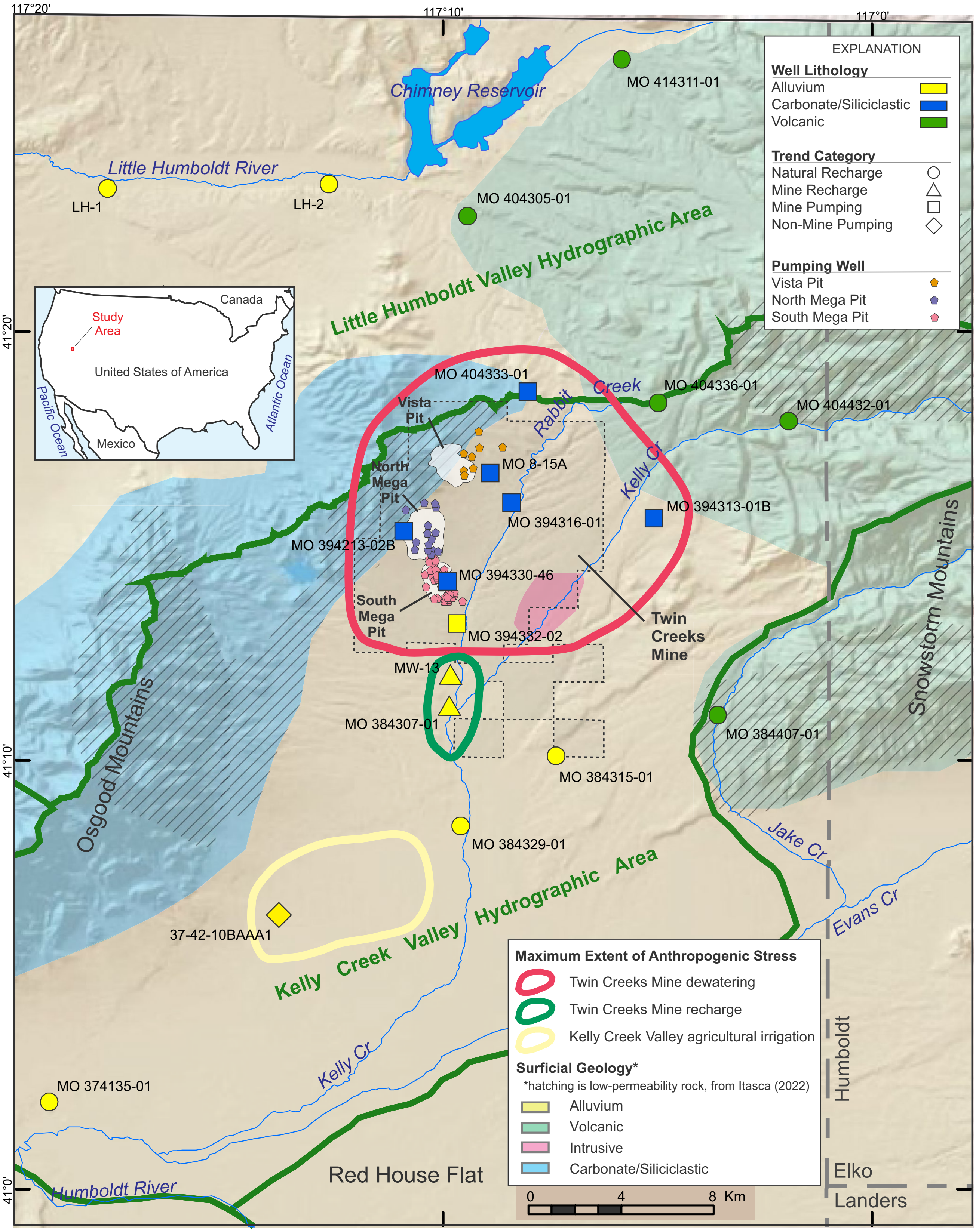

Fig. 1 Study-area wells in monitoring network for Twin Creeks Mine, north-central Nevada, USA

shale, siltstone, and sandstone. Paleozoic rocks form a fractured bedrock aquifer, which receives groundwater recharge directly at outcrops within highland areas (Fig. 1), or indirectly from overlying alluvial or volcanic aquifers. Tertiary volcanics consist of fractured rhyolitic, andesitic, and basaltic lava flows, which occur throughout the Snowstorm Mountains. Tertiary volcanics receive groundwater recharge from outcrops in the Snowstorm Mountains.

In Kelly Creek Valley HA, groundwater flows from highland recharge areas in the Osgood and Snowstorm Mountains toward the Kelly Creek valley floor (Fig. 1). Groundwater beneath Kelly Creek valley flows south-southwest toward the Humboldt River. In Little Humboldt Valley HA, groundwater derived from the northern parts of the Osgood and Snowstorm Mountains flows northward to discharge along the Little Humboldt River.

Groundwater – Surface Water Interactions

The headwaters of Jake Creek occur in the Snowstorm Mountains, and streamflow from the mountain front traverses low-permeability volcanic rock that maintains surface-water flow in the creek (Itasca 2022). Farther downgradient, the creek crosses into alluvium and is a losing reach that recharges the alluvial groundwater system (Fig. 1).

The headwaters of Kelly and Rabbit Creeks also occur in the Snowstorm Mountains. Only the upper parts of the creeks maintain perennial flows. Flow in Rabbit Creek are artificially supplemented near South Mega Pit by discharge of treated water from mine dewatering operations (Fig. 1). Surface water from the two creeks reaches the Humboldt River only during exceptionally wet periods (Itasca 2022). Most of the time, water in the channels recharges the alluvial groundwater system and then discharges downgradient from phreatophytes near the Humboldt River.

The Humboldt River is a losing reach along the southern boundary of Kelly Creek Valley HA, whereas the Little Humboldt River is a gaining reach near Chimney Creek Reservoir (Itasca 2022). Water levels in Chimney Creek Reservoir change in response to variations in precipitation, reservoir water storage, and irrigation usage.

Mine Dewatering and Rabbit Creek Discharge

Gold was discovered at the location of the Mega Pits in 1984, but mining operations did not begin until 1987. From 1987 to 2022, dewatering occurred during mining of the Mega Pits, where annual pumping rates were between 0.2 and 9 million cubic meters per year (Mm^3/yr). Open pit and underground mining began at Visita Pit in 2012, with dewatering rates ranging from 9.2 to 17.3 Mm^3/yr between 2012 and 2022.

Excess groundwater withdrawals, which are not used for mine-water consumptive use, undergo water treatment prior to discharge to Rabbit Creek. Water discharged to Rabbit Creek was from Mega Pit dewatering wells prior to 2012, and mostly from Vista Pit dewatering wells after 2012. Discharged water to Rabbit Creek infiltrates into the alluvium upstream of the Humboldt River (Itasca 2022). Estimated Rabbit Creek discharges have ranged from 0.9 to 3.6 Mm^3/yr prior to 2012 and from 3 to 6.8 Mm^3/yr between 2012 and 2022 (Itasca 2022).

Methods

Compiled datasets required to determine aquifer stresses include precipitation data, Chimney Creek Reservoir storage volumes, measured water levels in wells, Kelly Creek Valley HA irrigation pumping rates, the TC Mine dewatering rates, and the TC Mine dewatering-discharge rates to Rabbit Creek. Natural recharge was estimated from precipitation data and Chimney Creek Reservoir storage volumes. The TC Mine water-level data, dewatering rates, and dewatering discharge to Rabbit Creek were retrieved from mine-site records and NDWR (2023).

Compiled Precipitation Data

Precipitation data were compiled from Winnemucca Airport precipitation station (Station ID: USW00024128; NOAA 2023b). Winnemucca Airport precipitation is assumed representative of Kelly Creek Valley HA precipitation and recharge patterns because the Winnemucca Airport station is (1) in close proximity (≈ 60 km) to the HA; and (2) at an altitude of 1311 m, which is similar to altitudes on Kelly Creek valley floor that range from 1300 to 1600 m. The Winnemucca Airport precipitation record is assumed to have a similar temporal distribution of wet and dry years, compared to areas surrounding the TC Mine.

Compiled Reservoir Storage Data

Chimney Creek Reservoir storage volumes were compiled from the Natural Resources Conservation Service database (Station ID: Chimney Creek Reservoir, Nevada; NRCS 2024). Chimney Creek Reservoir annual maximum storage volumes were used as a proxy for precipitation and recharge patterns in Little Humboldt Valley HA because: (1) no precipitation stations are available in Little Humboldt Valley HA and (2) reservoir storage volumes are assumed to be correlated with wet and dry years in the northern part of the study area (see next section for details).

Estimation of Natural Recharge

Thresholds of above-average, winter precipitation, and peak reservoir-storage volumes can be used as proxies for recharge events. Jackson et al. (2022) developed a statistics-based method for estimating precipitation thresholds that represent recharge events. This method requires computing a standardized precipitation index (SPI) from a long-term (20 + year) precipitation record. To calculate the SPI, long-term precipitation data are transformed using a Gamma distribution, then fitted to a normal distribution (Guttman 1999). These normally distributed SPI values range from − 3 to 3, where zero represents the long-term mean, and positive and negative values are the number of standard deviations from the mean (Guttman 1999; McKee et al. 1993). The SPI approach can also be applied to reservoir-storage volumes.

In Nevada, most recharge is derived during wet winters, when evapotranspiration is minimal (Smith et al. 2017; Winograd et al. 1998). Potential recharge in Kelly Creek Valley HA was estimated from the Winnemucca Airport precipitation record (1900–2023) by summing winter precipitation from October 1 to March 31 (Fig. 2a) and computing the winter SPI (Fig. 2b). Because wet climatic conditions are defined by an SPI greater than 1 (Guttman 1999), recharge from wet winters was assumed to correlate with winter SPI values greater than 1 (Fig. 2c). For example, there were 20 wet winters at Winnemucca Airport from 1900 to 2023, which represent years with potential recharge in Kelly Creek Valley HA; during the remaining 104 years, all winter precipitation is assumed to have evapotranspired (Fig. 2).

Potential recharge in Little Humboldt Valley HA was estimated from Chimney Creek Reservoir maximum storage volumes (Fig. 3a). SPI values were computed from annual maximum storage volumes (Fig. 3b), and wet climatic conditions were defined by SPI values exceeding 1 (Fig. 3c). For example, Chimney Creek Reservoir annual maximum storage volumes greater than 25 Mm^3 (SPI = 1) represent years where potential recharge occurred in Little

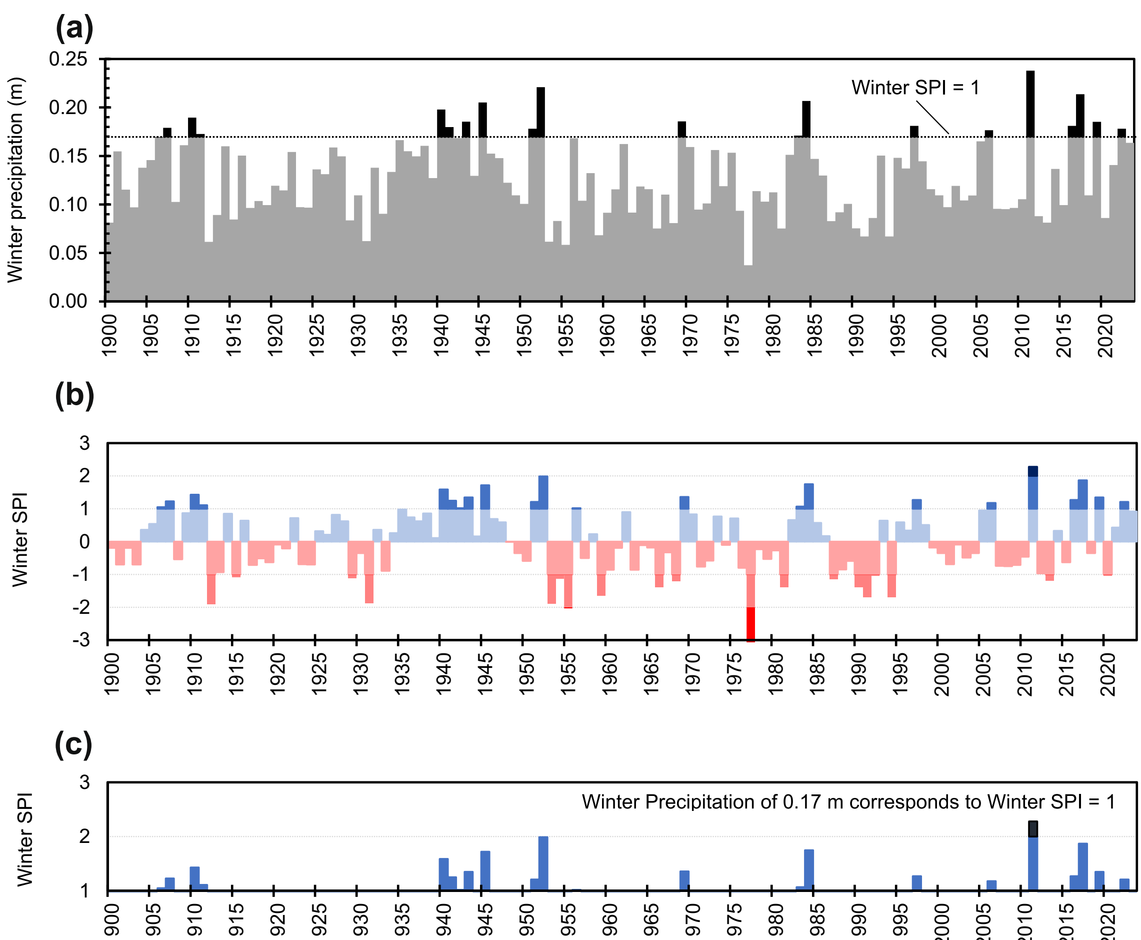

Fig. 2 Winnemucca Airport precipitation data: **a** Winter precipitation, summed from October 1 to March 31, **b** Winter Standardized Precipitation Index (SPI) computed using winter precipitation data, **c** Winter SPI values exceeding 1, which show the relative magnitude and temporal distribution of recharge events in Kelly Creek Valley HA

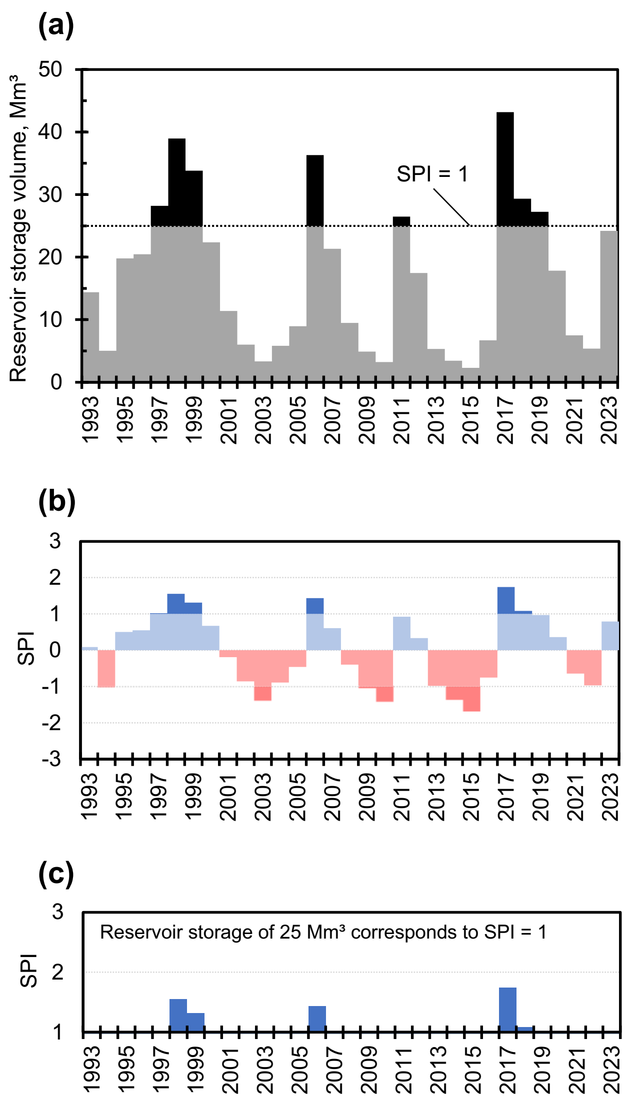

Fig. 3 Chimney Creek Reservoir data: **a** Annual maximum storage volumes, in millions of cubic meters (Mm^3), **b** Standardized Precipitation Index (SPI) computed using annual maximum reservoir-storage volumes, **c** SPI values greater than 1, which represent the relative magnitude and temporal distribution of recharge events in Little Humboldt Valley HA

Humboldt Valley HA (Fig. 3). The timing of wet winters from the Winnemucca Airport precipitation record is similar to the timing of high water-storage periods in the reservoir; however, SPI magnitudes differ. For example, between 1995 and 2023, 2011 was the wettest year in Kelly Creek Valley HA (Fig. 2c), whereas 2017 was the wettest year in Little Humboldt Valley HA (Fig. 3c).

Trend Analysis Approach

An analytical, curve-matching approach was used to fit a simulated curve to periodic, measured water-level data (Halford et al. 2012). The simulated curve is the summation of the hydrologic stresses that explain annual to multi-decadal water-level fluctuations in a well. Stresses considered were (a) dewatering from the TC Mine; (b) non-mine irrigation pumping in Kelly Creek Valley HA; (c) artificial recharge sourced from the TC Mine surface-water discharge into Rabbit Creek; (d) natural recharge, as determined from SPIs computed using winter precipitation data (Kelly Creek Valley HA; Fig. 2c) and Chimney Creek Reservoir storage-volume data (Little Humboldt Valley HA; Fig. 3c); and (e) natural aquifer drainage. Theis (1935) analytical solutions were used to transform pumping schedules from mine-dewatering and non-mine irrigation wells into pumping drawdown and recovery responses. Gamma distributions were used to transform natural and artificial recharge proxies into water-level responses. Natural aquifer drainage is analogous to an assumed, constant, regional groundwater discharge.

Theis Transform – Pumping

The Theis (1935) analytical solution solves for drawdown and recovery at a well, based on a specified pumping rate. Water-level changes from pumping were simulated using a Theis transform (Halford et al. 2012). A Theis transform is the resultant water-level curve from the superposition of multiple Theis solutions, based on monthly or annual pumping rates. Theis transforms have been demonstrated as a powerful way to simulate pumping-induced water-level changes, even in hydrogeologically complex mediums where the Theis solution's simplifying assumptions have been violated (Garcia et al. 2013).

Two hypothetical datasets are shown in Fig. 4 to demonstrate the use of Theis transforms. The hypothetical "measured data" were generated by summing the Theis transforms and then adding noise to the data using the random-number generator function in Microsoft Excel®. In the first example, consider a hypothetical monitoring well A (Fig. 4a), where water levels are affected by pumping from nearby well 1 (Fig. 4b). The simulated curve (Fig. 4a) is the Theis transform of three Theis (1935) solutions: one solution for each change in pumping rate at well 1 (Fig. 4b). In the second example, a hypothetical monitoring well B (Fig. 4c) has water levels affected by pumping from wells 1 (Fig. 4d) and 2 (Fig. 4e). In this example, multiple Theis (1935) solutions were superimposed to account for interference between the two pumping wells. Figure 4c is a simulated curve that is the summation of (1) one Theis transform composed of three Theis (1935) solutions for each of the three pumping rates

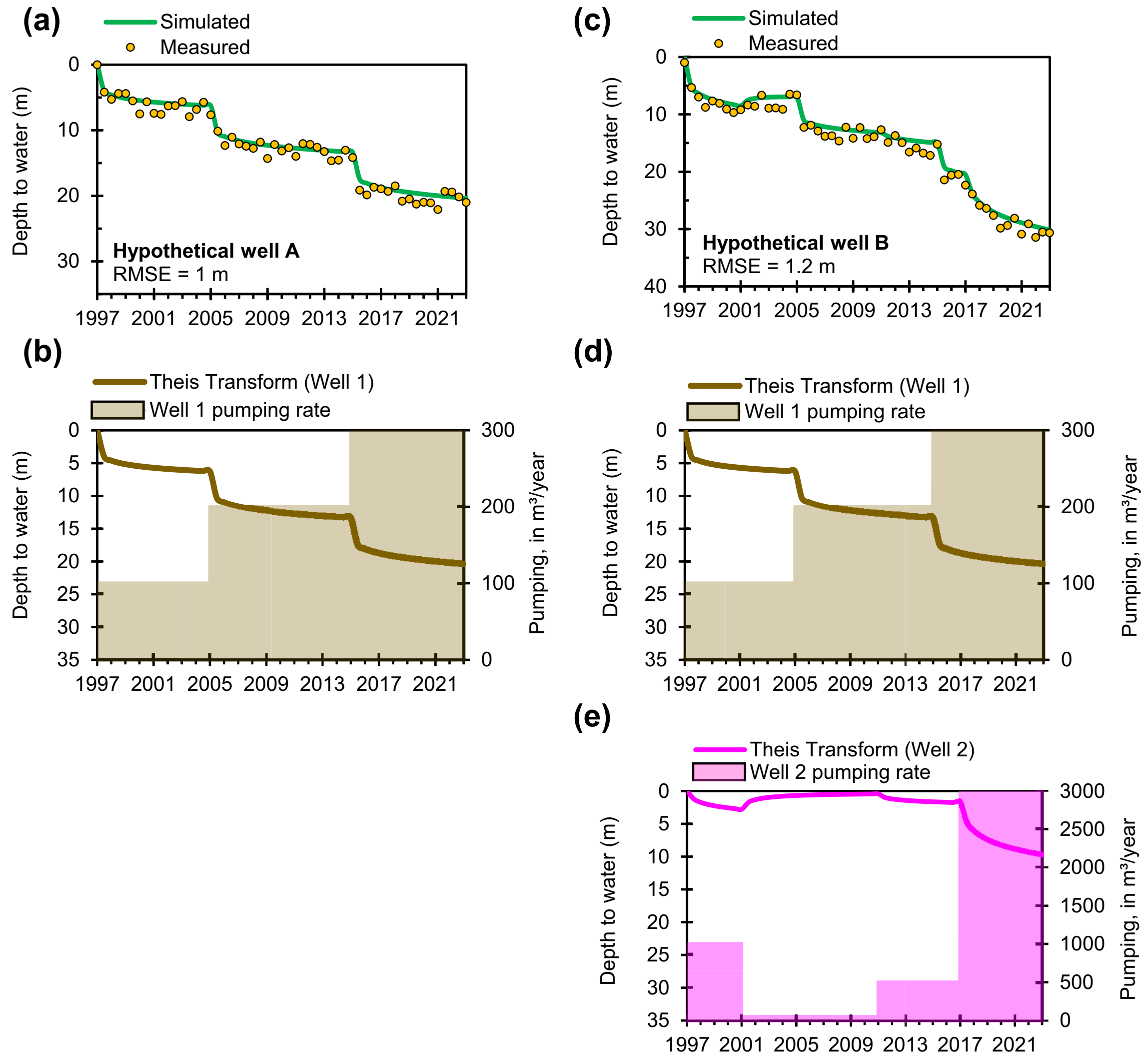

Fig. 4 Two hypothetical examples demonstrating use of Theis transforms: **a** Data from hypothetical well A fitted with one Theis transform from pumping at well 1, **b** Theis transform composed of three Theis (1935) solutions for well 1, **c** Data from hypothetical well B fitted with two Theis transforms for pumping at wells 1 and 2, **d** Theis transform composed of three Theis (1935) solutions for well 1, **e** Theis transform composed of four Theis (1935) solutions for well 2. RMSE is root-mean-square error

in well 1 (Fig. 4d) and (2) one Theis transform composed of four Theis (1935) solutions for each of the four pumping rates in well 2 (Fig. 4e).

The Theis solution uses radial distance, storativity, and transmissivity as fitting parameters. The first parameter, radial distance from the pumping well to the monitoring well, is known and fixed. The remaining two parameters are adjusted to optimize the match between simulated and measured water levels. Storativity and transmissivity have no physical meaning within the model and are simply fitting parameters (Halford et al. 2012). That is, storativity and transmissivity values in the model do not necessarily reflect actual aquifer properties because heterogeneity and anisotropy of the aquifer may violate the simplifying assumptions used in the Theis solution. Therefore, fitting parameters are not always synonymous with true aquifer storativity and transmissivity.

Gamma Transform – Recharge

The Gamma distribution can be used to simulate a water-level response from a recharge pulse (Aksoy 2000; Eagleson 1978; O'Reilly 2004; Markovic 1965). The shape of the Gamma distribution depends on the timing and magnitude of the recharge pulse and accounts for properties of the aquifer system, such as the thickness of the unsaturated zone, aquifer diffusivity, and lateral distance between the well and the recharge source (O'Reilly 2004). A recharge event, where SPI exceeds 1 (Figs. 2, 3), is used as the input variable for a Gamma distribution. Individual Gamma distributions from multiple recharge events are superimposed to form a Gamma transform. SPI values from 1980 to 2023 were used as an input parameter, where antecedent (1980–1994) data provide an initial condition to the period of record analyzed (1995–2023).

A hypothetical example is described below to demonstrate how winter SPI values are transformed to recharge responses using Gamma transforms (Fig. 5). For this example, the hypothetical "measured data" were generated by summing the Gamma transforms and then adding noise to the data using the random-number generator function in Microsoft Excel®. Hypothetical measured data in monitoring well C are affected solely by natural wet-winter recharge (Fig. 5a). The simulated water-level curve is the summation of three time-series components: (1) a Gamma transform representing rapid recharge responses; (2) a Gamma transform representing attenuated recharge responses; and (3) constant aquifer drainage (Fig. 5b).

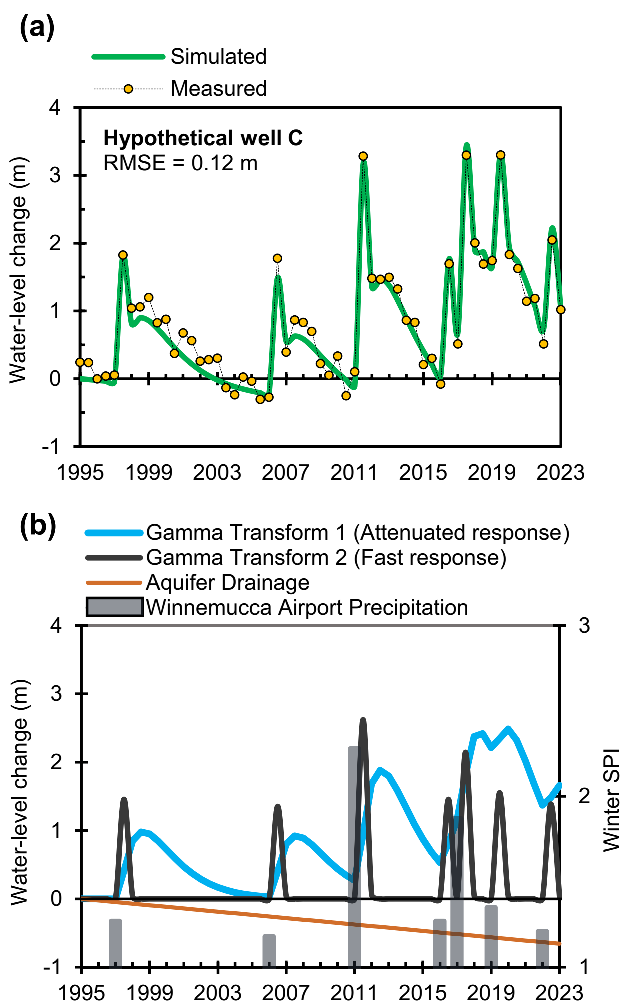

Fig. 5 Hypothetical example demonstrating use of Gamma transforms: **a** Data from hypothetical well fitted with simulated curve representing natural recharge and discharge, **b** Three time-series components representing attenuated recharge (Gamma transform 1), fast recharge (Gamma transform 2), and aquifer discharge. RMSE is root-mean-square error

Artificial recharge along Rabbit Creek from the discharge of excess dewatering water at the TC Mine also was simulated using the Gamma transform. Metered dewatering discharge to Rabbit Creek was used as a proxy for recharge, where periods of greater dewatering discharge are assumed to be correlated with greater amounts of surface-water infiltration along Rabbit Creek. As an example, Fig. 6 shows the results for study-area well MO 384307-01. Simulated and measured water levels compare favorably in well MO 384307-01 (Fig. 6a), where the simulated curve is the sum of natural recharge from wet winters (Fig. 6b), artificial recharge from mine-water discharge to Rabbit Creek (Fig. 6c), and natural aquifer drainage (Fig. 6d). Note that the purpose of the curve-matching approach is to replicate the general shape of the water-level trend to explain the dominant stresses affecting water levels at the well.

Aquifer Drainage

Aquifer drainage is synonymous with natural groundwater discharge, which occurs primarily as evapotranspiration from phreatophytes in the study area (Huntington et al. 2022). At every point in the groundwater system, groundwater is constantly moving (or draining) at a nearly constant rate toward the discharge area. A constant groundwater discharge (and aquifer drainage) rate is assumed because of long (10–40 km) distances between recharge and discharge areas, which causes the regional hydraulic gradient to be relatively constant with time.

The constant aquifer-drainage rate and long-term recharge rate were assumed to be equal. For Kelly Creek Valley HA, total recharge was estimated by summing winter precipitation above 0.17 m (i.e. winter SPI of 1) in the Winnemucca Airport precipitation record, which sums to 0.41 m. The total recharge (0.41 m) was divided by the 123-year estimation period (1900–2022) to estimate an aquifer-drainage rate of 0.003 m/yr. The aquifer-drainage rate (0.003 m/yr) was divided by an effective porosity to translate the rate into a water-level decline. Effective porosity was a calibration parameter that was allowed to vary from 0.1 to 0.2 for wells open to basin fill and from 0.01 to 0.05 for wells open to fractured rocks.

Calibration

The simulated curve is the summation of natural and artificial recharge responses represented by Gamma transforms, a constant aquifer-drainage rate represented by a sloping linear line, and pumping-drawdown and recovery

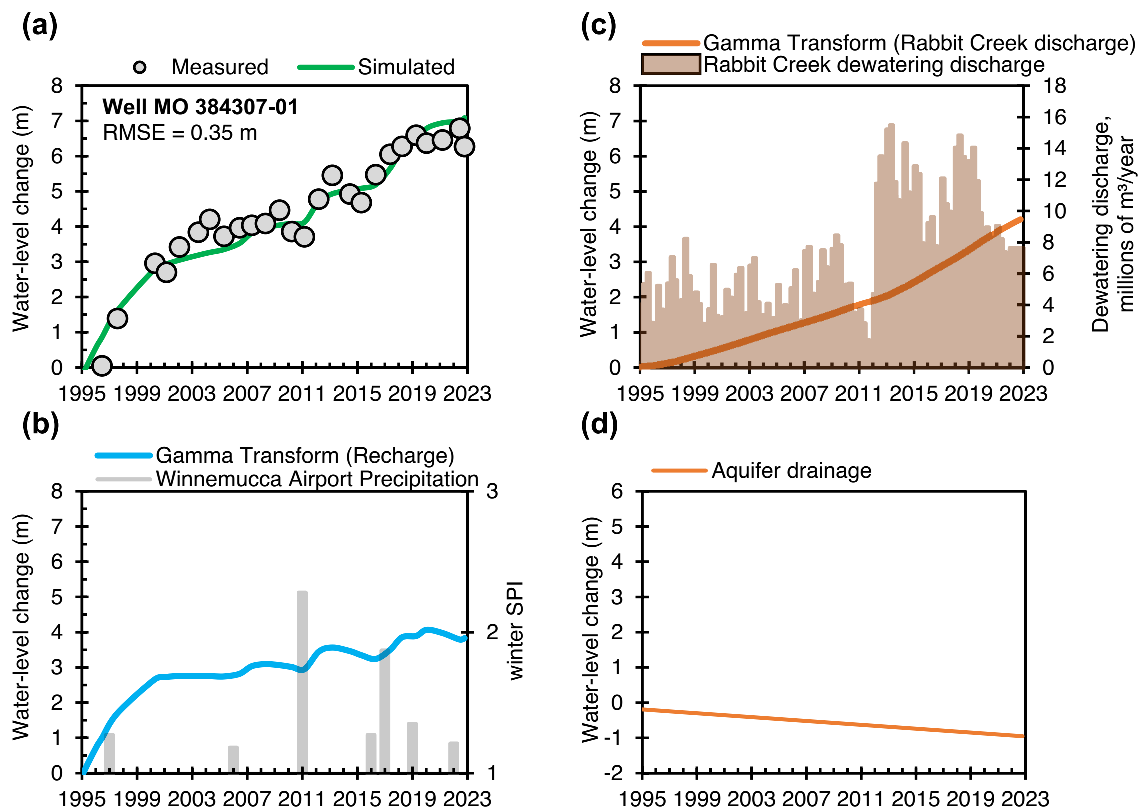

Fig. 6 Study-area well MO 384307-01: **a** Comparison of simulated and measured water levels, **b** Winter SPI values (data input) and resulting Gamma transform, representing water-level response to recharge, **c** Metered dewatering discharge from TC Mine to Rabbit Creek (data input) and resulting Gamma transform, representing water-level response to artificial recharge, **d** aquifer drainage. RMSE is root-mean-square error

responses represented by Theis transforms. Microsoft Excel® workbooks, equipped with VBA code, were used to fit simulated and measured water levels. For each well, a simulated curve was matched to measured water levels using automated parameter estimation with the Microsoft Excel® solver add-in. Parameters adjusted include the shape, scale, and amplitude of the Gamma transforms, the effective porosity of the aquifer-drainage line, and the transmissivity and storativity of Theis transforms. Simulated and measured water levels were fitted until residual differences were minimized, as quantified by the root-mean-square error (RMSE). All measured water levels were weighted equally in this study; however, lower weights can be assigned to individual spurious, poor-quality measurements. The RMSE ranged from 0.35 to 2.8 m for well hydrographs affected by natural and artificial recharge, where maximum water-level changes were less than 9 m within the analysis period (1995–2023). The RMSE ranged from 0.17 to 8.9 m for well hydrographs affected by pumping, where larger RMSEs occurred for wells with larger water-level changes.

Results

A water-level trend analysis was used to correlate water-level rises and declines in wells with hydrologic stresses acting on the groundwater system. Trend-analysis results were categorized by the predominant stress affecting water levels in each well. Stresses affecting wells were used to delineate the approximate extent of mine and non-mine pumping and the extent of artificial recharge to Rabbit Creek.

As part of the trend analysis, a conceptual model was developed to understand the baseline water-level trend, so that natural trends can be recognized and differentiated from trends likely affected by anthropogenic stresses. Therefore, the baseline trend is presented first and is followed by results of the water-level trend analysis.

Baseline Water-Level Trend of Study Area

A conceptualization is developed herein to understand the expected water-level trend from natural fluctuations in the groundwater system. Over short-term (annual to decadal) periods, water levels fluctuate in response to natural groundwater recharge and discharge. As stated earlier, natural groundwater discharge is relatively constant with time. Therefore, short-term water-level fluctuations in wells are primarily caused by temporal variability in recharge. Over long periods, cumulative recharge and discharge balance, such that there is no change in groundwater storage. Developing a baseline water-level trend using the concept of dynamic equilibrium requires an assumed long-term timescale. A scale on the order of a century is used here because the study area has large groundwater basins with long distances between recharge and discharge areas (Itasca 2022).

A century-scale recharge pattern was approximated for the study area using the winter SPI computed from the long-term (1900–2023) Winnemucca Airport precipitation record (Fig. 7a). Recharge was estimated as winter precipitation in excess of 0.17 m (i.e. SPI exceeding 1). Below 0.17 m, all winter precipitation was assumed to be evapotranspired. Note in Fig. 7a that the temporal recharge distribution estimated for the study area does not reflect the absolute magnitude of recharge. Instead, the recharge distribution reflects the relative magnitude and pattern of occurrence. Based on Fig. 7a, the study area has experienced decadal dry and wet periods, with the most notable wet periods occurring in the 1940s and after 2010.

A baseline water-level trend was constructed from cumulative recharge and discharge over an assumed 123-year period of dynamic equilibrium (Fig. 7b). Cumulative recharge is the sum of winter precipitation exceeding 0.17 m (i.e. winter SPI of 1) (Fig. 7a). As shown in Fig. 7b, total cumulative aquifer discharge (– 0.5 m) is assumed equal in magnitude to total cumulative recharge (0.5 m), where the aquifer-discharge rate declines linearly. The baseline trend was computed by summing annual cumulative recharge and discharge and dividing by 10% effective porosity (Fig. 7b). The assumed effective porosity is not important for this analysis because the effective porosity does not affect the timing of water-level rises and declines in the baseline trend.

The baseline water-level trend shows the expected, natural water-level trend since 1900, where the net change in water level is zero (Fig. 7b). The baseline record indicates that, during the first part of the twentieth century, a declining trend likely occurred from 1910 to 1940 because of an absence of wet winters, which was followed by a rising trend during a wet period in the 1940s. Infrequent wet winters from 1950 to 2010 result in brief periods of water-level rise superimposed on a long-term declining trend (Fig. 7b). Post-2010, natural water-level fluctuations are expected to have upward trends because of more frequent wet winters (Fig. 7b). Study-area wells unaffected by anthropogenic effects are expected to have similar trends to the baseline trend. However, measured water-level trends will vary slightly from the baseline trend because of factors that include variable aquifer hydraulic diffusivities, distance between wells and recharge source(s), and unsaturated-zone thickness.

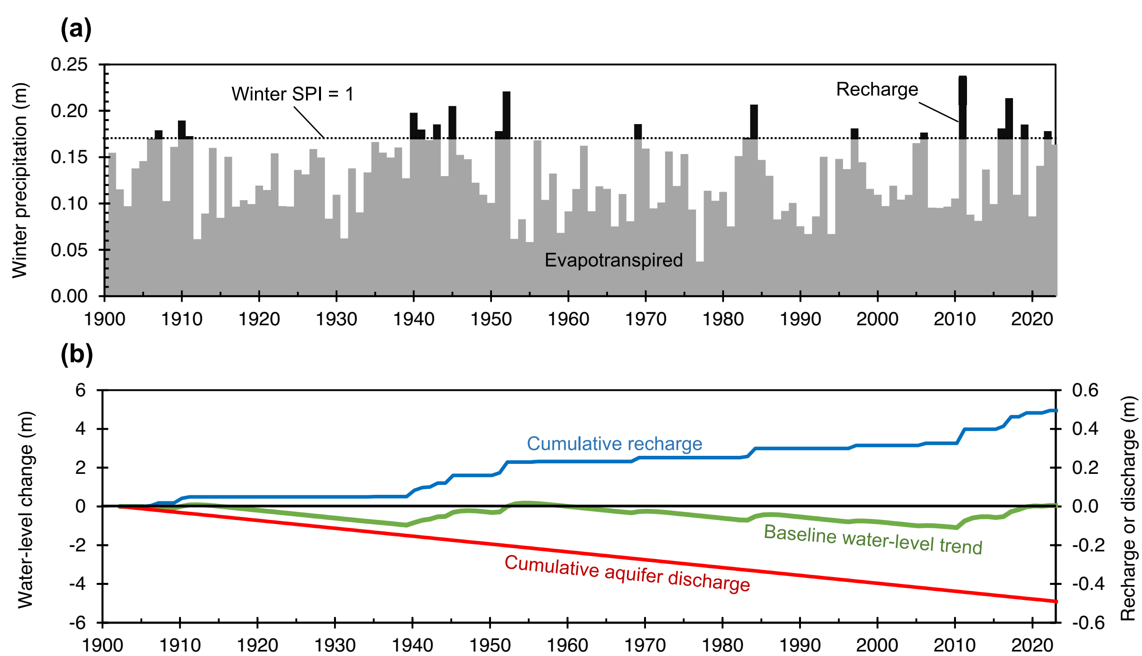

Fig. 7 Baseline water-level trend for the study area, 1900–2023: **a** Estimated winter-recharge distribution, **b** Century-scale baseline water-level trend computed from cumulative recharge and discharge

Natural Recharge Trends

Water levels in wells affected only by natural recharge and discharge have trends that are consistent with the baseline water-level trend developed for the study area. For example, the baseline water-level trend has a hummocky declining trend from 1995 to 2010 and a rising trend post-2011 (Fig. 7b). Measured water-level trends in six wells within Kelly Creek Valley HA exhibit this same pattern (Fig. 8).

The simulated curves replicate the general shape of natural water-level trends for all wells shown in Fig. 8. These study-area wells are near ephemeral channels (Fig. 1), where water levels have responded to runoff events from the 1997, 2006, 2011, 2016, 2017, and 2019 wet winters. Small misfits between simulated and measured water levels occur because a single temporal recharge distribution is used for these wells, when relative magnitudes of recharge differ spatially across Kelly Creek Valley HA. Despite these small misfits, the overall correlation between water-level responses and wet winters indicate that Winnemucca Airport precipitation is a representative proxy of recharge within Kelly Creek Valley HA.

In Little Humboldt Valley HA, the simulated curves replicate the general shape of natural water-level trends for all wells shown in Fig. 9. These study-area wells are near the Little Humboldt River and Chimney Creek Reservoir (Fig. 1). Water-level trends indicate that water levels rose during wet periods spanning 1995–2000 and 2016–2019, and water levels declined in the intervening dry periods. Well hydrographs show long-term declining trends (Fig. 9), which are attributed to a declining limb of recharge following the wet period in the late-1990s.

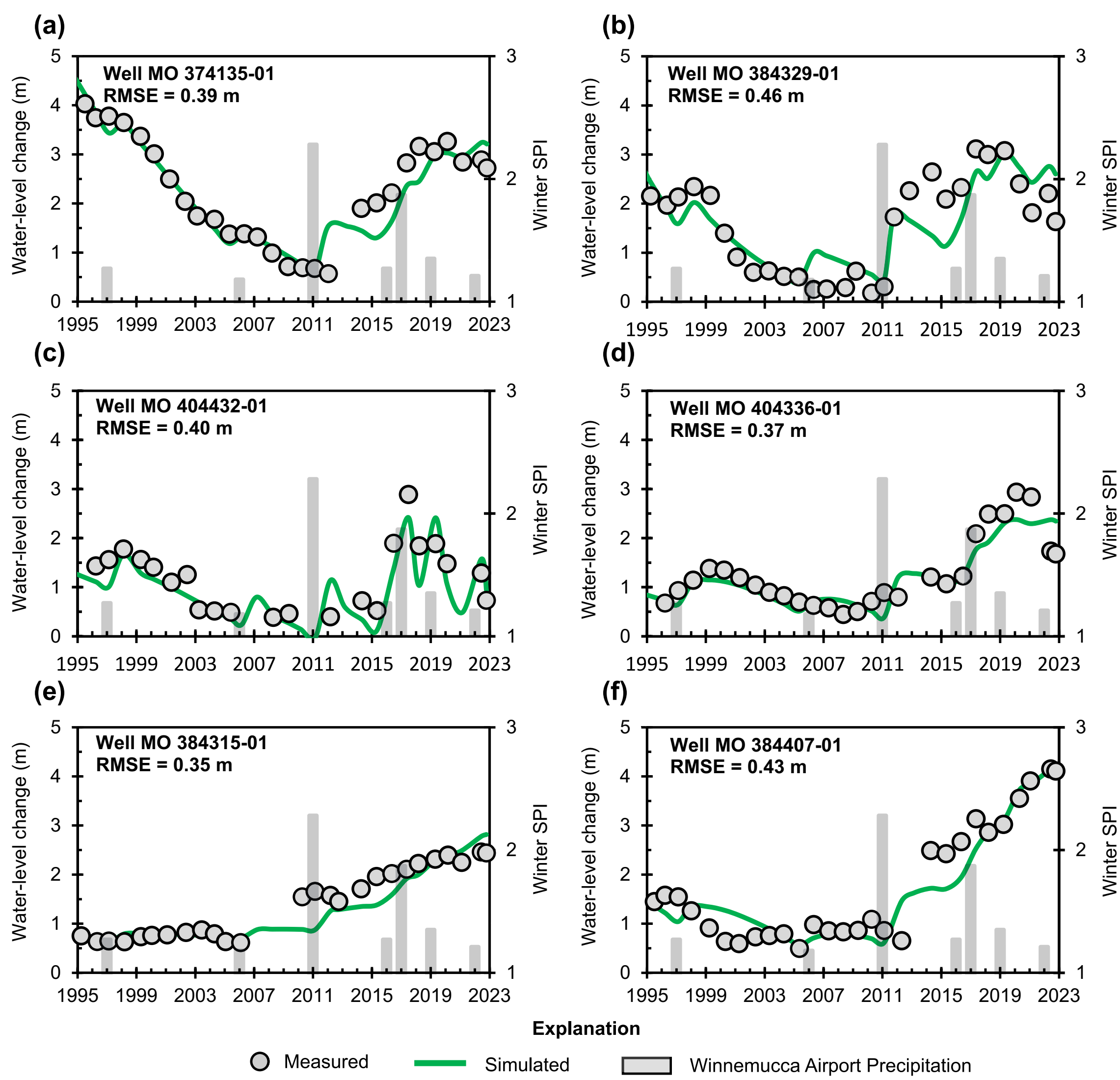

Fig. 8 Comparison of simulated and measured water levels for six wells in Kelly Creek Valley hydrographic area affected only by natural recharge and discharge. RMSE is root-mean-square error

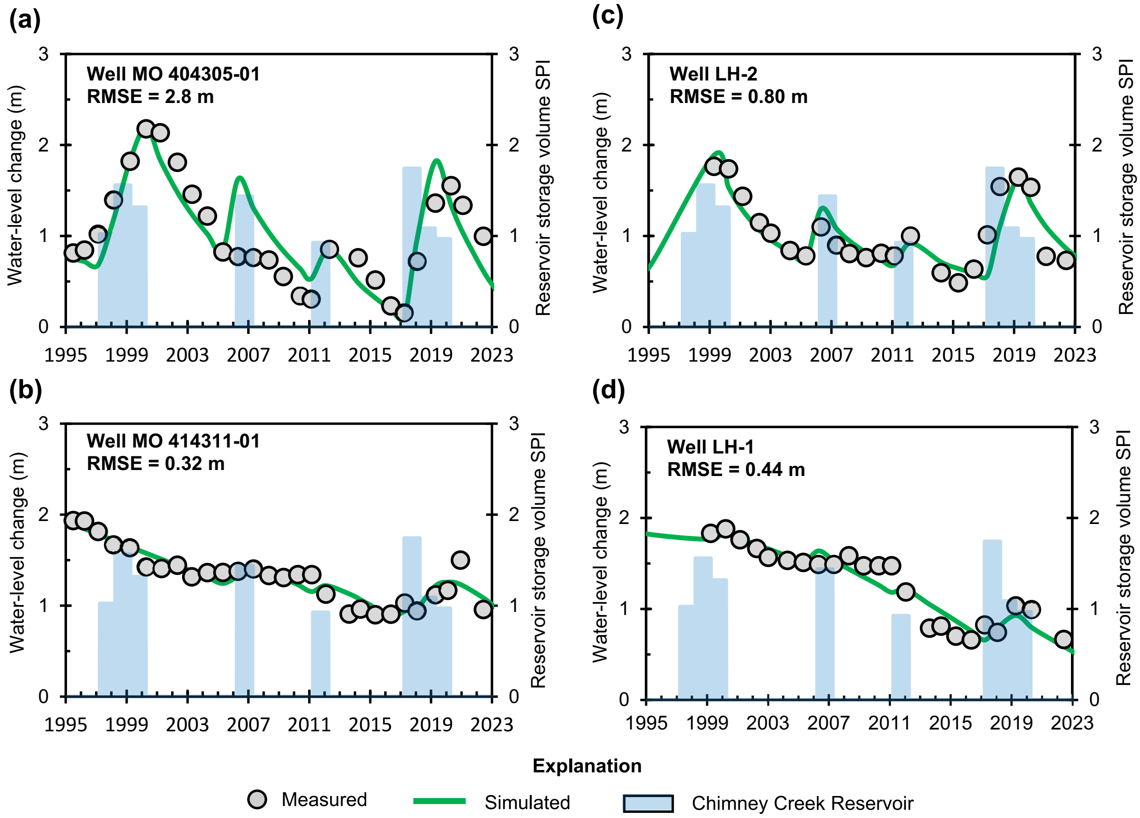

Fig. 9 Comparison of simulated and measured water levels for four wells in Little Humboldt Valley hydrographic area affected only by natural recharge and discharge. RMSE is root-mean-square error

A notable misfit occurs between simulated and measured water levels for the 2007 wet winter in well MO 404305-01 (Fig. 9a). The misfit occurs because precipitation and recharge were not uniform across Little Humboldt Valley HA and peak flows from Chimney Creek Reservoir do not capture the exact pattern of temporal recharge in all wells. However, the 2007 non-declining trend in well MO 404305-01 indicates that recharge was occurring, even if the recharge response could not be adequately simulated because of the recharge proxy used.

Mine-Sourced Recharge Trends

Wells MW-13 and MO 384307-01 are near Rabbit Creek, immediately downgradient of where treated dewatering water from the TC Mine is discharged into the creek (Fig. 1). Simulated and measured water-level trends compare favorably for the two Rabbit Creek wells (Fig. 10). Trend-analysis results indicate that, post-2000, both wells are largely affected by surface-water infiltration of the TC Mine dewatering discharge to the creek, with a smaller influence from natural recharge (Fig. 6). The dewatering discharge sustains the long-term rising trend in wells MW-13 and MO 384307-01 from 1995 to 2023.

Twin Creeks Pumping Trends

Pumping wells at the TC Mine were grouped into three dewatering areas: Vista Pit, North Mega Pit, and South Mega Pit (Fig. 1). Water-level responses to pumping were simulated with one Theis transform for each of the three dewatering areas. Wells MO 8-15A (Fig. 11a) and MO 394313-01B (Fig. 11b) are near Vista Pit and their measured trends can be replicated with one Theis transform that simulates Vista Pit dewatering. Likewise, well MO 394330-46 is adjacent to North Mega Pit and the pumping-drawdown and water-level recovery responses are attributed only to North Mega Pit dewatering (Fig. 11c). Well MO 394213-02B is within the highwall of North Mega Pit and is open to low-permeability Paleozoic rocks (Fig. 1). Water-level rises and declines in well MO 394213-02B are responses to pumping from a single dewatering well, DW-73, in the North Mega Pit area (Fig. 11d). This dewatering well is a about 1 km north of well MO 394213-02B. Trend-analysis results demonstrate that a measured trend in a well can be attributed to an individual dewatering well or multiple pumping wells in a dewatering area.

Well MO 394332-02 is about 1- and 2-km south of South and North Mega Pit dewatering areas, respectively

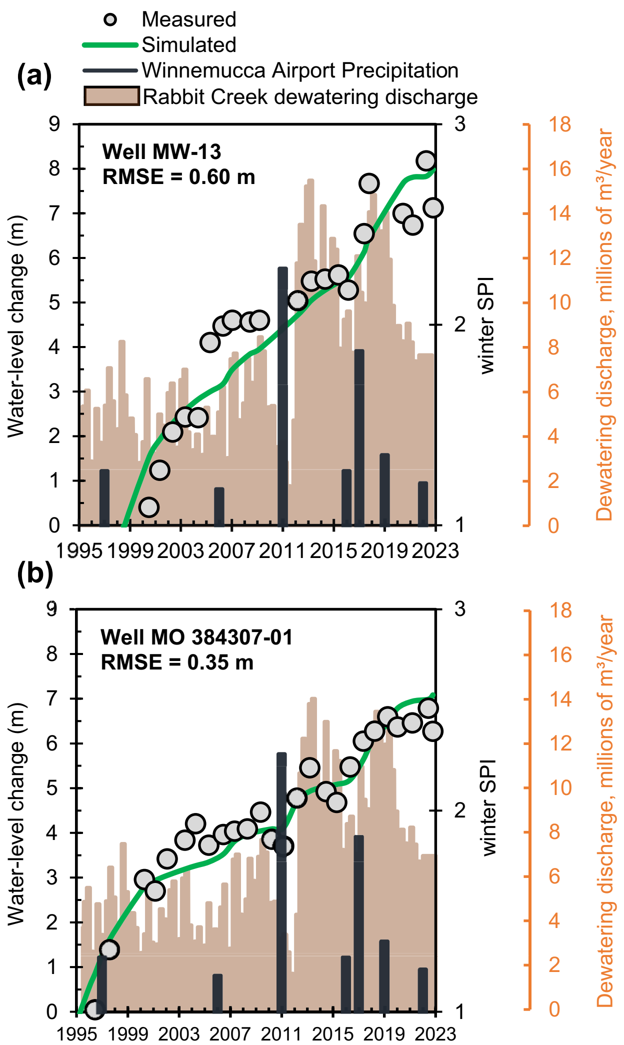

Fig. 10 Comparison of simulated and measured water levels for two Rabbit Creek wells affected by the TC Mine dewatering discharge and natural recharge and discharge. RMSE is root-mean-square error

(Fig. 1). The simulated curve replicates the general water-level trend in well MO 394332-02 (Fig. 12a) and indicates that the well hydrograph has been affected by South and North Mega Pit dewatering (Fig. 12b, c). The timing of pumping-drawdown and water-level recovery in well MO 394332-02 are consistent with the cessation of South Mega Pit mining and decreased dewatering in 2006 (Fig. 12b). Measured water-level recovery is attenuated by long-term water-level declines from North Mega Pit dewatering (Fig. 12c).

Wells MO 404333-01 and MO 394316-01 are about 3.5 and 6.3 km north and east of Vista Pit dewatering wells, respectively (Fig. 1). Water levels in well MO 404333-01 are predominantly affected by Vista Pit dewatering with a smaller contribution to total drawdown from North Mega Pit dewatering (Fig. 13a–c). Water levels in well MO 394316-01 are nearly equally affected by Vista and North Mega Pit dewatering (Fig. 13d–f).

Non-Mine Irrigation Pumping Trends

Well 37-42-10BAAA1 is near a non-mining irrigation area in Kelly Creek Valley HA (Fig. 1). The simulated curve indicates that this well is affected only by Kelly Creek Valley irrigation pumpage (Fig. 14). A distal mine-dewatering response at well 37-42-10BAAA1 can be ruled out because nearby wells MO 384329-01 and MO 384315-01, which are between the TC Mine and the irrigation area, are affected only by natural stresses (Fig. 8). Furthermore, well MO 394332-02 is just south of Mega Pit dewatering (Fig. 1), has a different trend (e.g. rising since 2009; Fig. 12), and the magnitude of drawdown in this nearfield well is similar to the much more distant well, 37-42-10BAAA1.

Extent of Mining and Non-Mining Effects on Groundwater System

The approximate extent of the TC mine-induced pumping was determined from analysis of water-level data. Any well identified as being affected by mine dewatering, as determined from trend-analysis results, was used to delineate the extent of TC pumping (Fig. 1). The mine-induced pumping extent delineated in this study is consistent with results from an InSAR-based subsidence analysis (Bell and Katzenstein 2011) and a groundwater-flow model (Itasca 2022). Kelly Creek Valley irrigation pumping is an isolated pumping center (Fig. 1), and TC Mine dewatering has not propagated more than about 5 km from the mine site. Mine-induced recharge from the TC Mine dewatering discharge to Rabbit Creek has a localized effect on groundwater levels above the confluence with Kelly Creek (Fig. 1).

Discussion

Gamma Distribution

The Gamma distribution is a powerful shape curve that can simulate a variety of water-level trend shapes for a given recharge distribution input. However, the power of the Gamma distribution is that it can only match a water-level trend if the timing and (or) magnitude of recharge events and dry periods correlate with subsequent water-level rises and declines. For example, the years when recharge occurred are consistent between Kelly Creek Valley and Little Humboldt Valley HAs (Figs. 2c, 3c), but the relative magnitudes of recharge differ for each year. This difference is reflected in observed water-level trends within the two HAs. Natural water-level trends from 1995 to 2023 in Kelly Creek Valley

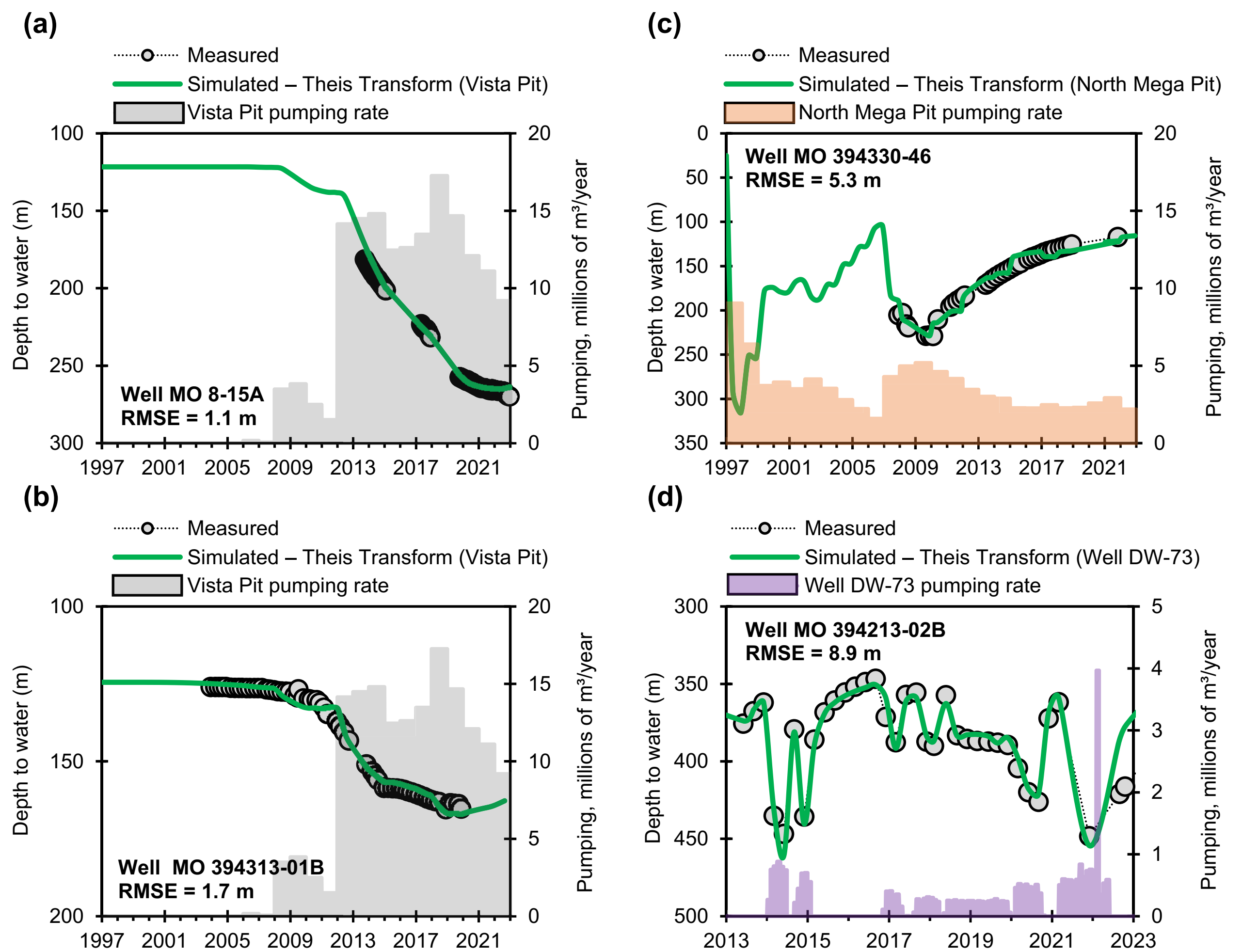

Fig. 11 Comparison of simulated and measured water levels for the TC Mine wells affected by a single mine-pumping area or a single mine-pumping well. RMSE is root-mean-square error

HA (Fig. 8) and Little Humboldt Valley HA (Fig. 9) indicate that the largest rises occurred in 2011 and 2017, respectively, consistent with the wettest year estimated for each HA (Figs. 2c, 3c). Therefore, the Gamma transform is constrained within the trend-analysis approach when identifying natural recharge.

Trend Analysis Approach Strengths and Limitations

The trend-analysis approach demonstrated herein does not require pre-existing knowledge of aquifer geometry, such as lateral and vertical extent or local heterogeneities. Theis and Gamma transforms can replicate water-level changes from pumping and recharge stresses, respectively (Figs. 8, 9, 10, 11, 12, 13, 14), and these transforms work well irrespective of hydrogeologic complexity or aquifer geometry (Garcia et al. 2013; O'Reilly 2004). Only an understanding of the geologic unit open to the well is required to provide an appropriate range of effective porosities, which differ between fractured bedrock and primary-porosity alluvial or tuffaceous sediments.

The approach is data-driven; therefore, the fit of the simulated curve to the data is only as good as the measured water-level data and data inputs. Misfits between simulated and measured water levels occur primarily from: (a) inherently messy periodic water-level measurements (Milliken and Johnson 2009); (b) errors in metered pumping rates and discharge rates to Rabbit Creek; and (c) if a recharge proxy is imperfect for the study area.

Precipitation-derived recharge will differ subtlety within each hydrographic area; however, a single recharge proxy was used in each area for simplicity and because of data limitations. For example, no precipitation stations occur in Little Humboldt Valley HA and Chimney Creek Reservoir storage-volume data were used to estimate wet periods from 1995 to 2023. Peak reservoir-storage volumes are an imperfect recharge proxy that affects the fit of simulated curves to measured data. By way of illustration, when viewing

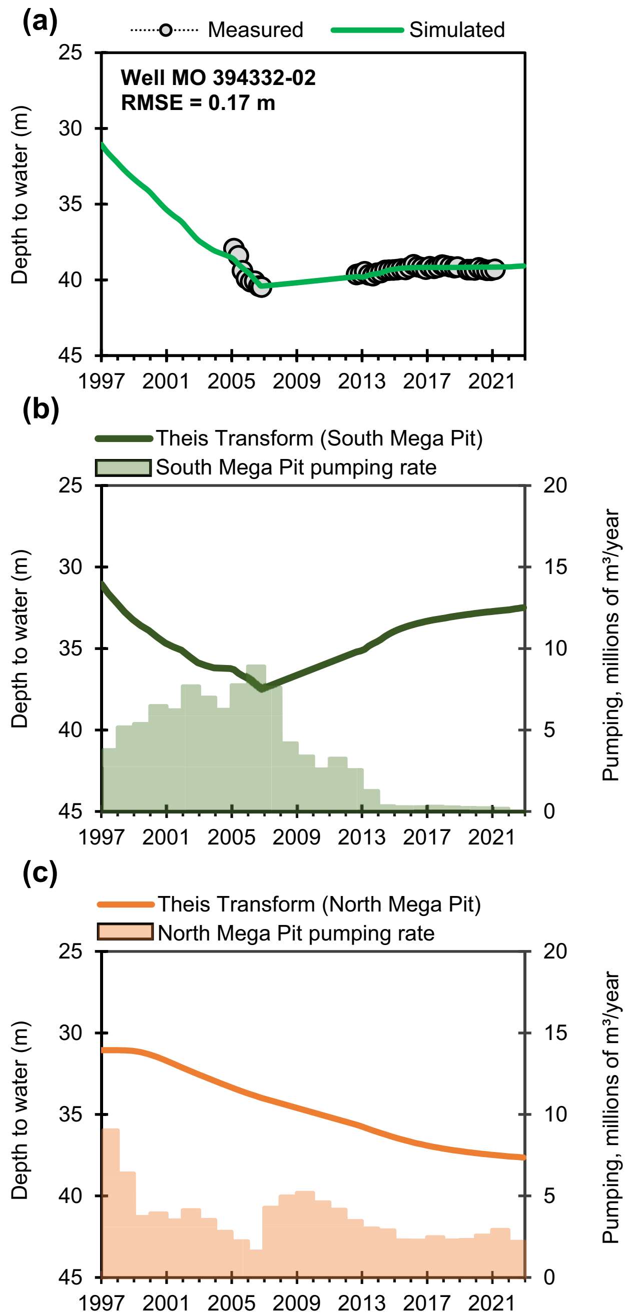

Fig. 12 Trend analysis of well MO 394332-02: **a** Comparison of simulated and measured water levels, **b** South Mega Pit pumping rates (data input) and resulting Theis transform, **c** North Mega Pit pumping rates (data input) and resulting Theis transform. RMSE is root-mean-square error

the fit of simulated curves to natural trends in Little Humboldt Valley HA (Fig. 9), notice that the 2007 wet winter induced either a small rising trend (Fig. 9b, c) or briefly stabilized a longer declining trend (Fig. 9a, d). Despite use of an imperfect recharge proxy, the simulated curves replicate the general shapes of natural water-level trends (Fig. 9). Likewise, for six wells in Kelly Creek Valley HA (Fig. 8), small misfits between simulated and measured water levels are attributed to variations in relative recharge magnitudes along ephemeral channels between highland areas and the valley floor. However, simulated curves replicate the general pattern of the natural trends in Kelly Creek Valley HA (Fig. 8), demonstrating that water levels are controlled by wet winter recharge. To summarize, when evaluating natural trends, a user of this approach should base their interpretation on matching the general shape of the trend and use the constructed baseline water-level trend for the study area as a guide.

Statistical Trend Analysis Pitfalls

Trend-analysis results using the curve-fitting approach were compared to statistical methods to demonstrate the pitfalls of interpreting water levels based on monotonic trends. The statistical methods of Mann–Kendall trend test, Kendall tau, and Sen's slope were applied to Kelly Creek Valley HA (Fig. 8) and Little Humboldt Valley HA (Fig. 9) wells that had been identified as having water-level trends affected only by natural stresses. Statistical analysis results are presented in Table 1. Statistical results indicate that Little Humboldt Valley wells LH-1, LH-2, and MO 414311-01 have statistically significant downward trends (Table 1). However, trend-analysis results of these wells with downward trends (Fig. 9) demonstrate that water levels declined in response to natural stresses and were not a result of pumping. Therefore, caution should be used when interpreting the meaning of statistically significant downward trends because not all declining trends are indicative of pumping.

A Note on Numerical Groundwater Models

Numerical groundwater-flow models provide limited information when evaluating water-level data to understand natural fluctuations. This is because most groundwater models simulate the predevelopment setting as a steady-state condition and the estimated recharge distribution is a long-term steady-state condition. Therefore, the steady-state model is assuming dynamic equilibrium and simulates constant water levels because there is no change in groundwater storage. Few groundwater models have the capability to adequately simulate time-varying recharge because little to no water-level data are available to constrain model-estimated recharge estimates.

Most transient groundwater models are used to simulate pumping responses and do not account for time-varying recharge. In a transient groundwater model that only simulates pumping, if the natural trend is a long-term decline because of drought conditions, the model can erroneously simulate the decline as pumping, especially if the natural

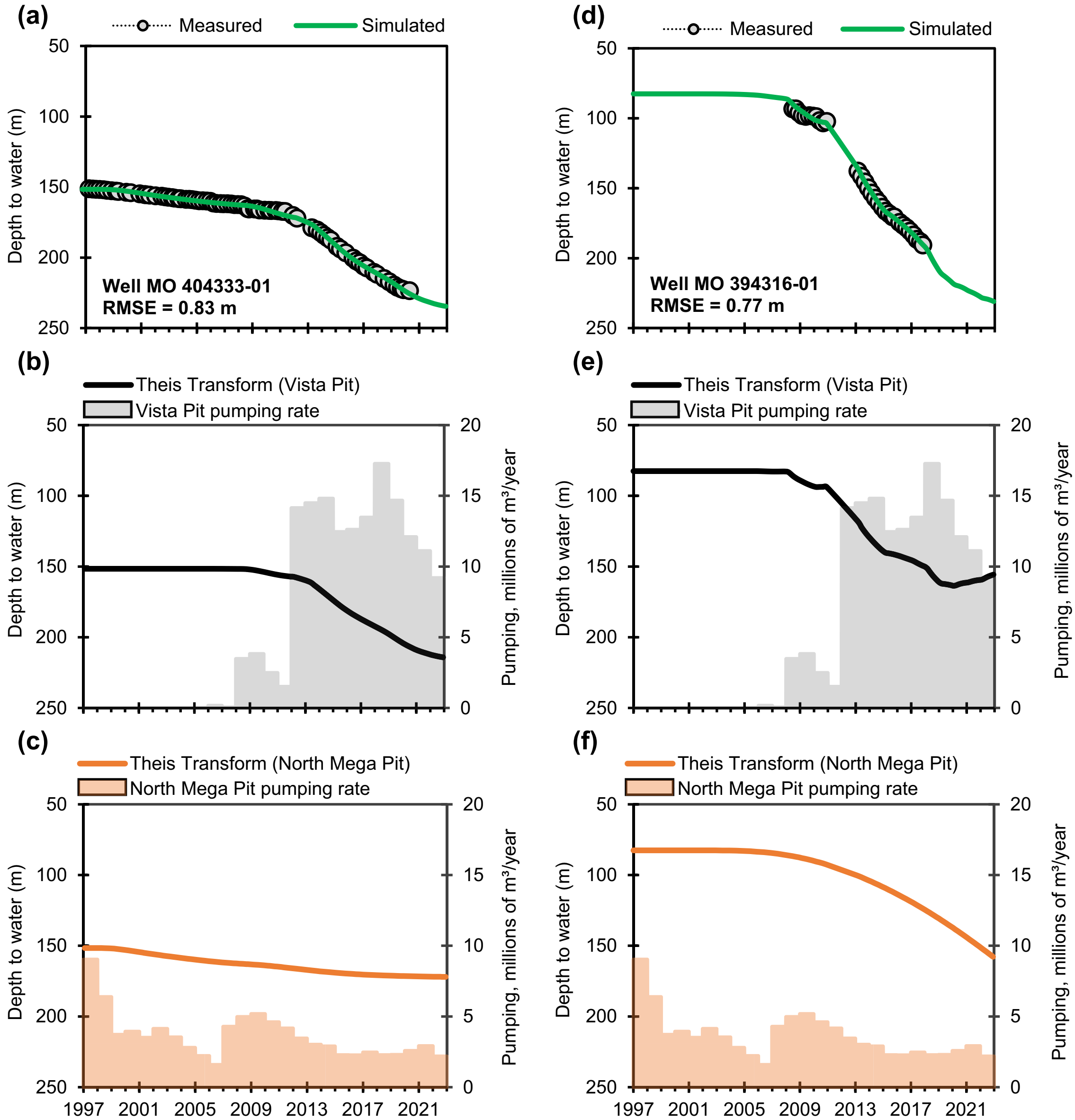

Fig. 13 Trend analyses of study-area wells distant from TC Mine: **a** Comparison of simulated and measured water levels in well MO 404333-01, **b** Vista Pit pumping rates (data input) and resulting Theis transform for well MO 404333-01, **c** North Mega Pit pumping rates (data input) and resulting Theis transform for well MO 404333-01, **d** Comparison of simulated and measured water levels in well MO 394316-01, **e** Vista Pit pumping rates (data input) and resulting Theis transform for well MO 394316-01, **f** North Mega Pit pumping rates (data input) and resulting Theis transform for well MO 394316-01. RMSE is root-mean-square error

declining trend dataset is provided as a calibration target. Therefore, the onus is on the modeler to recognize natural trends and use these datasets accordingly. For example, a natural declining trend can be used as a calibration target, with the caveat that the water levels are representing a zero-drawdown condition. As shown from this example, proper evaluation and interpretation of water-level data should be done prior to importing water-level data into a groundwater-flow model as calibration targets. Estimating the baseline trend and using a curve-matching trend analysis approach to assess water-level data will avoid simulation of erroneous drawdown extents, especially in areas distant from the mining operation.

Value of Curve-Matching-Type Water-Level Trend Analyses

The water-level trend analysis approach described herein is a fast, simplistic approach to: (1) identify erroneous data; (2) reconcile water level and pumping datasets; (3)

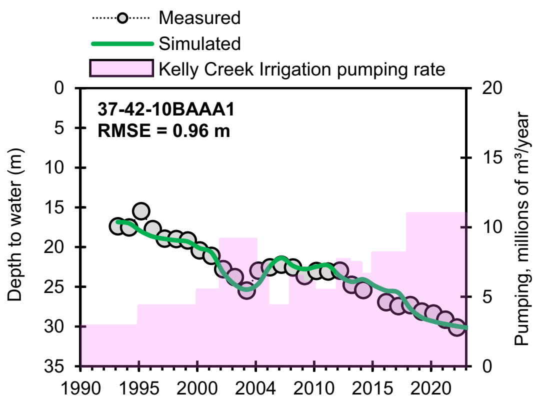

Fig. 14 Comparison of simulated and measured water levels at well 37-42-10BAAA1, affected by non-mine irrigation pumping in Kelly Creek Valley HA. RMSE is root-mean-square error

develop a hydrologic conceptualization of a study area; and (4) address questions related to hydrologic stresses likely affecting water-level trends. Nuanced data errors resulting from pressure-transducer drift can be identified to determine when the drift began and to flag erroneous data. Human errors in manual measurements within long-term records can also be identified and removed, such as transposing numeric values or accidentally adding the data from one well to another. For monitoring wells near a dewatering area, an analytical curve-matching approach can be used to determine if reported aggregate dewatering rates are likely in error. The approach also is useful in the development of groundwater models by evaluating whether water-level trends are affected by pumping, natural stresses, or both.

For a mine site near a protected surface water or groundwater-dependent ecosystem, the mine operator is frequently required to report the following to one or more regulatory agencies (and key stakeholders): mine-site data related to water levels, mine groundwater withdrawals, and mine discharges to the environment. Regulatory review of mine-site data is done to assess whether a mine is impacting nearby water users or protected ecosystems. The mine operator must be able to successfully determine if a well is affected by mine dewatering and, if water levels are not affected, then to provide an explanation for the hydrologic stresses that are affecting water levels in a well. A trend analysis that uses a data-driven, curve-matching approach is a simplistic, yet defensible, method to address mine-related effects on the environment.

Conclusions

This study couples a baseline trend estimation method with a trend-analysis approach to analyze water-level trends in wells. The trend-analysis approach is a simple, but defensible, curve-matching method to understand all natural, mining, and non-mining stresses affecting water levels in wells. The approach was applied to the water-level monitoring network at the Twin Creeks Mine in north-central Nevada, USA. Stresses identified in the study-area wells include natural recharge, recharge sourced from

Table 1 Statistical analysis results for wells identified as having water levels affected only by natural stresses

Hydrographic area	Well	Mann–Kendall trend test[1]	Kendall's tau[2]	Level of significance (p)[3]	Sen's slope[4]	Statistically significant trend[5]
Kelly Creek Valley	MO 384407-01	H = 1	0.49	0.0003	2.8E−04	Up
	MO 404432-01	H = 0	− 0.04	0.82	− 1.4E−05	None
	MO 404336-01	H = 1	0.33	0.02	1.3E−04	None
	MO 384315-01	H = 1	0.79	0.00000002	2.0E−04	Up
	MO 384329-01	H = 0	0.15	0.25	5.1E-05	None
	MO 374135-01	H = 0	− 0.20	0.15	− 1.0E−04	None
Little Humboldt Valley	LH-1	H = 1	− 0.78	0.0000003	− 1.5E−04	Down
	LH-2	H = 1	−0.41	0.008	− 1.5E−04	Down
	MO 414311-01	H = 1	− 0.63	0.00001	− 9.2E−05	Down
	MO 404305-01	H = 1	− 0.34	0.02	− 7.7E−05	None

[1]Tests null hypothesis (H = 0), indicating an absence of a trend. Rejection of null hypothesis (H = 1) indicates a statistically significant trend

[2]Measures strength of monotonic trend. Values range between − 1 (strong declining trend) and 1 (strong rising trend), with zero indicating no monotonic trend

[3]p values less than (<) 0.001 have high statistical significance; p values < 0.01 are considered statistically significant

[4]Increasing trends have positive values, whereas declining trends have negative values

[5]Considered significant if (1) Mann–Kendall trend test rejects null hypothesis (H = 1); (2) p value < 0.01; and (3) Kendall's tau is greater than 0.4; up, down, and none mean rising, declining, and no trend, respectively

mine-dewatering discharge to Rabbit Creek, mine dewatering, and non-mine irrigation pumping. Results of the analysis were used to delineate the approximate extent of mining and non-mining pumping effects on the groundwater system and indicated that the two pumping areas have not coalesced.

The curve-matching trend-analysis approach requires the development of a baseline water-level trend for the study area to understand expected natural water-level fluctuations. The baseline trend is developed for a natural condition that assumes long-term dynamic equilibrium, where long-term net changes in groundwater levels are zero. The concept of dynamic equilibrium requires an assumed steady-state timescale. The timescale length can be correlated with groundwater-basin size and hydrologic setting. For example, semi-arid to arid environments have larger basins with long distances between recharge and discharge areas, resulting in longer groundwater residence times and steady-state timescales, as demonstrated in this study. Once a timescale is assumed, a recharge proxy for the study area is required. This study demonstrates the development of natural recharge proxies using winter precipitation data and peak reservoir storage volumes, and an artificial recharge proxy using metered dewatering-discharge rates to a surface-water channel. Recharge proxies also could be constructed using long-term streamflow records or reservoir-stage data.

Results were compared between the curve-matching trend-analysis approach and statistical methods (e.g. Mann–Kendall trend test, Kendall tau, or Sen's slope). The curve-matching approach indicated that 10 study-area well hydrographs have natural trends, and statistical methods identified three of these wells as having statistically significant downward trends. Comparison between these approaches demonstrates that not all water-level declines are induced by pumping and caution should be used when interpreting the meaning of statistically significant downward trends, because the downward trend may be climate driven.

The curve-matching trend-analysis approach can be used for other applications, such as identifying and removing erroneous data, reconciling complimentary datasets (e.g. water-level and pumping data), or building a hydrologic conceptualization of the area. The approach also provides insight into temporal and spatial recharge trends, and the extent of mining and non-mining effects on the groundwater system. Even though a numerical groundwater-flow model can be developed to estimate the current drawdown extent from mine-induced pumping, a curve-matching trend-analysis approach can provide similar results at less cost. Furthermore, relying only on a groundwater-flow model to differentiate natural and anthropogenic effects can go awry because a model can be forced into a condition that simulates all water-level declines as pumping-induced, even if the decline in a well is not related to pumping.

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