23692 Birtcher Drive
Lake Forest CA 92630

949.420.3030 phone
530.756.5991 fax
westyost.com

TECHNICAL MEMORANDUM

DATE: May 5, 2022

Project No.: 941-80-21-68
SENT VIA: EMAIL

TO: Peter Kavounas, Chino Basin Watermaster

FROM: Garrett Rapp, PE, RCE #86007
Eric Chiang, PhD
Lauren Sather, PhD

SUBJECT: Proposed Updated Methodology to Calculate the Safe Yield of the Chino Basin

This technical memorandum (TM) documents West Yost's findings related to the development of an updated Safe Yield Reset methodology. This TM is prepared pursuant to the scope of work[1] to comply with the April 28, 2017 Court Order regarding the Safe Yield of the Chino Basin (2017 Court Order).[2]

1.0 BACKGROUND AND OBJECTIVES

Watermaster's Optimum Basin Management Program (OBMP) Implementation Plan called for an initial redetermination of the Safe Yield in 2011 using monitoring data collected during the period of 2001 through 2010.[3] This was incorporated as a requirement in Watermaster's Rules and Regulations.[4] In 2012, Watermaster began an investigation to recalculate the Safe Yield of the Chino Basin, which was completed in 2015. The investigation developed and implemented a methodology to calculate Safe Yield and concluded that the Safe Yield for the period of fiscal year (FY) 2011 through 2020 was 135,000 afy (WEI, 2015).[5] The methodology used to calculate the Safe Yield was approved in the 2017 Court Order and is described below:

> *"The methodology to redetermine the Safe Yield for 2010/11 and the recommended methodology for future Safe Yield evaluations is listed below. This methodology is consistent with professional custom, standard and practice, and the definition of Safe Yield in the Judgment and the Physical Solution.*
>
> 1. *Use the data collected during 2000/01 to 2009/10 (and in the case of subsequent resets newly collected data) in the re-calibration process for the Watermaster's groundwater- flow model.*

[1] The scope of work is described in Exhibit B of West Yost's October 29, 2021 letter here: link

[2] *Orders for Watermaster's Motion Regarding the 2015 Safe Yield Reset Agreement, Amendment of Restated Judgment, Paragraph 6,* Superior Court for the County of San Bernardino (2017). link

[3] OBMP Implementation Plan, p. 44-45, Program Element 8 – Develop and Implement Groundwater Storage Management Program, Program Element 9 – Develop and Implement Storage and Recovery Program

[4] See Section 6.5 of the June 2001 Chino Basin Watermaster Rules and Regulations.

[5] The report *2013 Groundwater Model Update and Recalculation of the Safe Yield Pursuant to the Peace Agreement* can be found here: link

2. *Use a long-term historical record of precipitation falling on current and projected future land uses to estimate the long-term average net recharge to the Basin.*
3. *Describe the current and projected future cultural conditions, including, but not limited to the plans for pumping, stormwater recharge and supplemental-water recharge.*
4. *With the information generated in [1] through [3] above, use the groundwater-flow model to redetermine the net recharge to the Chino Basin taking into account the then existing current and projected future cultural conditions.*
5. *Qualitatively evaluate whether the groundwater production at the net recharge rate estimated in [4] above will cause or threaten to cause "undesirable results" or "Material Physical Injury". If groundwater production at net recharge rate estimated in [4] above will cause or threaten to cause "undesirable results" or "Material Physical Injury" then Watermaster will identify and implement prudent measures necessary to mitigate "undesirable results" or "Material Physical Injury", set the value of Safe Yield to ensure there is no "undesirable results" or "Material Physical Injury", or implement a combination of mitigation measures and a changed Safe Yield."*

In addition to approving the current Safe Yield Reset methodology, the 2017 Court Order included provisions regarding potential future updates to the Safe Yield Reset methodology:

> *"4.4 Safe Yield Reset Methodology. […] In furtherance of the goal of maximizing the beneficial use of the waters of the Chino Basin, Watermaster, with the recommendation and advice of the Pools and Advisory Committee, may supplement the Reset Technical Memorandum's methodology to incorporate future advances in best management practices and hydrologic science as they evolve over the term of this order."*

Page 17 of the 2017 Court Order requires that "[t]he Pools be provided with reasonable opportunity, no less frequently than annually, for peer review of the collection of data and the application of the data collected in regard to" the update of the Safe Yield Reset methodology and the other requirements set forth in the 2017 Court Order.

The Safe Yield of the Chino Basin was recalculated in May 2020 using the 2020 Chino Valley Model (2020 CVM) and documented in the *2020 Safe Yield Recalculation Report* (2020 SYR Report) (WEI, 2020).[6] The Court adopted a Safe Yield of 131,000 acre-feet per year for the period of FY 2020/21 through 2029/30.[7] To aid the development of the 2020 CVM and its application to recalculate the Safe Yield, Watermaster conducted several peer review/stakeholder workshops for the Parties and their invited technical consultants. The questions and comments that arose during the review process were recorded and responded to in writing in Appendix F of the 2020 SYR Report. Several of these comments and questions are related to the Safe Yield Reset methodology and can be grouped into the following two categories:

- Recommendations to characterize and address uncertainty in the 2020 CVM and SYR methodology.
  - Uncertainty in groundwater model parameters (Appendix F-6, page 2-3; Appendix F-6, page 25)
  - Uncertainty in historical data (Appendix F-6, page 14)

---

[6] The *2020 Safe Yield Recalculation Report* can be downloaded here: link

[7] *Orders for Watermaster's Motion Regarding the 2020 Safe Yield Reset Agreement, Amendment of Restated Judgment, Paragraph 6,* Superior Court for the County of San Bernardino (2020). link

- Uncertainty in supply and demand projections (Appendix F-2, page 4; Appendix F-2, page 8; Appendix F-4, page 4; Appendix F-6, page 2-3; Appendix F-6, page 20)
- Uncertainty in projected hydrology and human behavior (Numerous)

- Recommendations to reconsider the 10-year prospective calculation of the Safe Yield (Appendix F-5, page 1; Appendix F-5, page 3; Appendix F-6, page 22; Appendix F-7, page 1-2)

1.1 Scope of Work to Update the Safe Yield Reset Methodology

In FY 2020/21 and early FY 2021/22, Watermaster and the Parties collaborated to develop and refine a scope of work to update the Safe Yield Reset methodology pursuant to the 2017 Court Order and the above recommendations of the Parties. The initial scope of work comprised the following steps:

1. Watermaster's Engineer will develop a technical memorandum (TM) defining the various sources of modeling uncertainty that should be considered and addressed in an updated Safe Yield Reset methodology, including related questions necessary to answer when updating the Safe Yield Reset methodology. This TM will be submitted to the Parties for review and comment.
2. Watermaster's Engineer will conduct a peer review meeting to discuss the content of the TM described in Step 1. Feedback gathered from the peer review committee will inform the development of a process to define the proposed approaches to address the sources of model uncertainty in the proposed Safe Yield Reset methodology update.
3. Watermaster's Engineer will prepare responses to the comments received from the peer review committee and prepare a supplemental scope and budget for the process to define and document the proposed approaches to address model uncertainty. Watermaster will introduce this supplemental scope and budget as a budget amendment to be approved through the Watermaster process.

The TM described in Step 1 was distributed to the Parties on October 21, 2021. The peer review meeting described in Step 2 was held on October 26, 2021. The supplemental scope and budget described in Step 3 was introduced to the Watermaster Pool Committees, Advisory Committee, and Board in November 2021 and was approved by the Watermaster Board on November 18, 2021. The remaining steps in the scope of work include:

4. Watermaster's Engineer will complete a survey of the state-of-the-art approaches to address the sources of uncertainty identified in the TM described in Step 1 (i.e., model parameters, water supply/demand projections, and climate projections). This will include the alternative approaches and datasets suggested in the October 26, 2021 peer review meeting. Watermaster's Engineer will choose up to three approaches for each source of uncertainty to define in the next step.
5. Watermaster's Engineer will define a method to implement each of the approaches selected in Step 4. Each method will consist of detailed steps for implementation in the calculation of the Safe Yield.

6. Watermaster's Engineer will quantify the feasibility of the methods defined in Step 5. This will involve (i) testing the chosen methods and amending them as needed; (ii) determining the necessary computational capabilities necessary to implement the methods (e.g., parallel computing); and (iii) developing a general analysis of costs (e.g., staff time, computational resources) and benefits for each of the proposed methods. Sub-steps (i) and (ii) pertain to parameter uncertainty only. These estimates will aid in a comparison and selection of a preferred updated Safe Yield Reset methodology.
7. Watermaster's Engineer will prepare a TM documenting the findings from Steps 4 through 6 and a recommended Safe Yield Reset methodology update. This TM will be reviewed with Watermaster staff before distributing to the Parties for review.
8. Watermaster will conduct multiple peer review workshops to solicit feedback on the TM and the recommended Safe Yield Reset methodology update. This step may include multiple iterations of the draft TM.
9. Following the completion of the peer review process, Watermaster's Engineer will finalize the TM prepared in Steps 7 and 8 and prepare a summary TM with the proposed Safe Yield Reset methodology for submittal to the Court.
10. Watermaster's Engineer will work with Watermaster staff and legal counsel to assist with the Court-approval process.

This TM completes Step 7 of the scope of work described above.

1.2 Outline of This TM

This TM includes the following sections.

- **Section 1: Background and Objectives**
- **Section 2: Overview of Uncertainty in Surface-Water and Groundwater Modeling.** This section provides an overview of the sources of uncertainty in surface-water and groundwater modeling as well as a description of best management practices published by the California Department of Water Resources (DWR) on how to address uncertainty in sustainable groundwater management.
- **Section 3: Uncertainty in the CVM and its Use in the Safe Yield Reset.** This section discusses the sources of uncertainty specific to the CVM and the Safe Yield Reset methodology.
- **Section 4: Potential Approaches for Characterizing and Addressing Uncertainty.** This section describes potential approaches and recommended methods to characterize and address uncertainty for updating the Safe Yield Reset methodology.
- **Section 5: Recommended Process for Calculating the Safe Yield.** This section describes the recommended Safe Yield Reset methodology update.
- **Section 6: Next Steps and Schedule.** This section describes the recommended next steps following the Peer Review meeting.
- **Section 7: References**

2.0 OVERVIEW OF UNCERTAINTY IN SURFACE-WATER AND GROUNDWATER MODELING

This section provides an overview of uncertainties in surface-water and groundwater modeling as well as a description of best management practices published by the DWR on how to address uncertainty in sustainable groundwater management.

Uncertainty analysis in calibration and projection is an important part of surface-water and groundwater modeling. Current practice in environmental impact assessments typically involves developing a single numerical groundwater model with limited uncertainty analysis. Considered in a risk management context, this approach is often insufficient to predict the range of potential impacts and their likelihood. A quantitative uncertainty analysis, however, delivers a range of model predictions (simulating historical or future conditions) with associated likelihoods, each plausible in that they are consistent with all available information and data. Uncertainty analysis also identifies the main sources of uncertainty and the extent to which the uncertainty in outcomes can be reduced by incorporating additional data into the model (Middlemis and Peeters, 2018). An uncertainty analysis of model parameters has the benefit of identifying gaps in data or understanding that may inform future monitoring (DWR, 2016). An uncertainty analysis of model projections improves the understanding of the sensitivity of modeled responses to future assumptions.

2.1 Sources of Uncertainty in Surface-Water and Groundwater Modeling

Groundwater management faces uncertainty on many fronts: in understanding the behavior of the groundwater system; in anticipating possible future climatic, economic, or geopolitical conditions; and in prioritizing management objectives, all of which combine to add ambiguity in the evaluation of management options (Guillaume, J. H. A., and others, 2016). For example, the subsurface environment is complex, heterogeneous, and difficult to directly observe, measure and characterize; and, groundwater systems are influenced by multiple factors, including geology, topography, vegetation, climate, hydrology, and human activities. Uncertainty in these factors affects our ability to accurately describe the existing groundwater system or predict its future state (Middlemis and Peeters, 2018).

Uncertainty in a model can be defined as the difference between the model and the complex physical system that the model represents. Since a mathematical model is a simplification of the complex system and processes, there will always be some difference between the model and reality (Johnson, J, 2010) and there will always be alternative models or model parameters that are plausible representations of the physical system. Uncertainty can be expressed in terms of the parameters used to describe the system or the accuracy in model predictions.

The remainder of this section summarizes the main sources of uncertainty in surface-water and groundwater modeling.

2.1.1 Historical Data

Historical data can be divided into two groups: (1) data that may be observed directly, such as precipitation, temperature, stream discharge, metered pumping, managed artificial recharge, wastewater discharge, and groundwater levels, and (2) data that cannot be or is not observed/measured directly, such as evapotranspiration, unmanaged recharge, septic tank discharge, unmetered pumping, and unmeasured applied water. Some data of the second group can be estimated based on other measurable data; for example, evapotranspiration can be estimated based on temperature, relative humidity, wind speed, net radiation, and crop type.

Historical data are used in groundwater models for various purposes, primarily for direct model inputs and model calibration. Some historical data are indirectly used to estimate parameters or boundary conditions in the model (e.g., using historical groundwater levels and borehole lithology to infer the hydraulic properties of a fault barrier). The quality of data used to build a model directly affects the quality of the model projection. Some of the types of historical data and their uses are listed in Table 1 below.

Table 1. Typical Historical Data used in Groundwater Models

Data Type	Purpose of Data	Use of Data in Model		
		Direct Input	Indirect Input	Model Calibration
Groundwater levels	Groundwater simulation		X	X
Groundwater pumping	Groundwater simulation	X		
Lithology and geologic data	Groundwater simulation	X	X	
Climatic data (precipitation, ET_0, temperature, evaporation, etc.)	Recharge estimation	X		
Ground elevation data	Recharge estimation		X	
Land use	Recharge estimation	X		
Stream discharge	Recharge estimation	X		X
Wastewater treatment plant influent	Recharge estimation			X
Water and wastewater infrastructure (sewersheds, water supply maps)	Recharge estimation		X	
Managed aquifer recharge	Recharge estimation/ groundwater simulation	X		X
Stream geometry	Recharge estimation/ groundwater simulation	X		
Wastewater treatment plant effluent	Recharge estimation/ groundwater simulation	X		

Model uncertainties related to historical data may exist due to: measurement error (e.g., inaccurate measurements of groundwater levels which hampers model calibration); lack of records (e.g., inadequate borehole data to describe the aquifer geometry and composition); inconsistent spatial resolution (e.g., paucity of groundwater-level data in areas or depths of the basin which hampers model calibration); and inconsistent temporal resolution (e.g., paucity of historical groundwater-level data which hampers model calibration).

2.1.2 Surface Water and Groundwater Model Parameters

Uncertainty exists in the ways that the physical environment is represented in a model. This includes: (1) hydraulic parameters (e.g., hydraulic conductivity, specific storage, specific yield) that govern the simulated behavior of the groundwater-flow system; (2) hydrogeologic features (e.g., aquifer geometry, hydrostratigraphy, barriers to groundwater flow) that are underground and are often not well understood; and (3) hydrologic processes (e.g., evapotranspiration, streambed recharge, and deep infiltration of precipitation and applied water) that are typically not measured directly. Initial estimated values of hydraulic parameters and parameters representing hydrogeologic features are usually assigned to a groundwater model during model construction. Parameters governing hydrologic processes are assigned to the surface-water and groundwater models. Hydraulic parameters, parameters representing hydrogeologic features, and parameters governing hydrologic processes are then adjusted during the calibration process that attempts to minimize the differences between observed historical data and the model-simulated data.

Another related problem regarding uncertainty in model parameters is the existence of non-unique solutions as demonstrated by Freyberg (1988) and Hunt et al (2020). Non-unique solutions of parameter combinations occur when there is more than one option for an unknown parameter that is being solved during the calibration process. The problem of non-uniqueness can result a model that meets calibration criteria but fails to adequately represent the real system.

2.1.3 Demand and Supply Plan Projections

The ability of a model to forecast the response of a groundwater system is not only dependent on the quality of the model calibration, but also is dependent on future surface and groundwater management projections. Long-term forecasts of water demands and available water supplies are critical inputs to water utility planning efforts and decision making (Kiefer, 2016). Forecasting water demands and supply plans is uncertain and influenced by macro-socioeconomic and climatic factors, as well as local behavior of consumers (Bruce, Brown, and Dufour, 2019).

In groundwater modeling, the projected water demand is coupled with a water-supply plan that assumes the use of various quantities of the available water sources, including groundwater pumping, local surface water, imported water, and recycled water. Wastewater disposal plans that describe the fate of the water supplied are also required to simulate the feedback between wastewater disposal and groundwater recharge. Translating the water supply and wastewater plans into groundwater model inputs also translates the uncertainty in these plans.

2.1.4 Projected Climate Impacts on Land Surface Processes

The climate directly and indirectly impacts the groundwater system through recharge and changes in water use in response to climate.

Currently, many studies on climate impacts rely on the projections of Global Circulation Models or Global Climate Models (GCMs) involved in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (Taylor and others, 2012). CMIP5 assumes four Representative Concentration Pathways (RCPs) that describe different climate futures, all of which are considered possible. In the near future, the projections of updated GCMs of the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (PCMDI, 2021) will replace those of CMIP5.

For use in SGMA-related water budget development and groundwater modeling, DWR provides climate change datasets in the form of change factors of precipitation, ET_0, and surface runoff based on 20 projections composed of 10 GCMs, each with two RCPs. According to the Guidance for Climate Data Change Use During Groundwater Sustainability Plan Development (DWR, 2018), change factor ratios were calculated as the future scenario (2030 or 2070) divided by the 1995 historical temperature detrended (1995 HTD) scenario. The 1995 HTD scenario represents historical climate conditions where the observed increasing temperature trend is removed. Review of the change factors for the Chino Valley indicated that that average precipitation is projected to decrease, and average reference evapotranspiration (ET0) is projected to increase (WEI, 2020). As with all model projections, the GCM projections are inherently uncertain.

Groundwater demands can change in response to climate, and the feedbacks between groundwater demands and climate must be considered in groundwater management. For example, California has taken multiple actions to address the recent drought. On April 1, 2015, Governor Jerry Brown released Executive Order B-29-15, which mandated a statewide reduction in urban potable water usage of 25 percent through February 2016. This resulted in several Chino Basin Parties to reduce their groundwater pumping, even though groundwater rights and storage accounts were unaffected by the order.

In 2018, the California legislature passed, and the Governor signed, two pieces of legislation (AB 1668 & SB 606) collectively known as "Making Conservation a California Way of Life" to establish new water efficiency standards for purveyors in response to the California drought. The legislation requires water suppliers to meet their supplier-specific urban water use objective starting in 2027, which is defined as a combination of objectives set for indoor residential water use, outdoor residential water use (ORWU), as well as other uses. The ORWU objective, which takes direction from previous legislation establishing California's Model Water Efficient Landscape Ordinance (MWELO), has not yet been approved by the State Water Board. However, DWR has proposed the following provisional method to calculate a supplier's ORWU (gallons) objective[8]:

$$ORWU = (ET_0 - P_{eff}) * ETF * LAs * 0.62$$

where, ET_0 is reference evapotranspiration (inches), P_{eff} is effective precipitation (inches), ETF is the supplier level evapotranspiration (ET) factor, LAs is landscape area (square ft) for a water supplier, and 0.62 is the unit conversion factor. If a supplier does not meet their ORWU objective by 2027, they may be required to reduce outdoor water use or be subject to penalties. A reduction in outdoor water use will reduce return flows from irrigation and precipitation (i.e., deep infiltration of precipitation and applied water [DIPAW]). In 2021, the DWR proposed a value of 0.7 for ETF. Additionally, the DWR is considering recommending that the value of ETF be reduced to 0.55 for any new development.

2.2 Modeling Best Management Practices for the Sustainable Groundwater Management Act

The Sustainable Groundwater Management Act (SGMA) was passed by the California legislature in 2014 "to support the long-term sustainability of California's groundwater basins". Pursuant to SGMA, the DWR published a series of Best Management Practices (BMPs) to aid Groundwater Sustainability Agencies (GSAs) and other stakeholders in efforts to meet the Groundwater Sustainability Plan (GSP) Regulations (DWR, 2016). The DWR's Modeling BMP (Modeling BMP) is meant to "assist with the use and development of groundwater and surface water models."

The Modeling BMP includes the following two recommendations for characterizing and addressing uncertainty.

1. ***Develop and run predictive scenarios that establish expected future conditions under varying climatic conditions, and implementing various projects and management actions.*** *Predictive scenarios should be designed to assess whether the GSP's projects and management actions will achieve the sustainability goal, and the anticipated conditions at five-year interim*

[8] DWR's proposed method is provisional because DWR is still finalizing the landscape area measurement data and considering stakeholder input.

milestones. Predictive scenarios for the GSP should demonstrate that the sustainability goal will be maintained over the 50-year planning and implementation horizon.

2. ***Conduct an uncertainty analysis of the scenarios.*** *This is to identify the impact of parameter uncertainty on the use of the model's ability to effectively support management decisions and use the results of these analyses to identify high priority locations for expansion of monitoring networks. Predictive uncertainty analysis provides a measure of the likelihood that a reasonably constructed and calibrated model can still yield uncertain results that drive critical decisions. It is important that decision makers understand the implications of these uncertainties when developing long-term basin management strategies. As discussed in other sections of this BMP, this type of analysis can also identify high-value data gaps that should be prioritized to improve confidence in model outputs, and yield a tool that has an increased probability of providing useful information to support effective basin management decisions. A formal optimization simulation of management options may be employed, taking advantage of the predictive uncertainty analysis to minimize economic costs of future actions, while meeting regulatory requirements at an acceptable risk level."*

The Chino Basin is adjudicated and therefore exempt from many of the requirements of SGMA including the need to develop a GSP. The groundwater and surface water models used in the Chino Basin have been approved for use by the Court. Furthermore, the groundwater models developed for GSPs are designed and interpreted to meet specific requirements of SGMA that are not entirely applicable to the Chino Basin. However, it is instructive to consider the above two recommendations when updating the Safe Yield Reset methodology, as they represent "best management practices" which are referenced in the 2017 Court Order.

3.0 UNCERTAINTY IN THE CVM AND ITS USE IN THE SAFE YIELD RESET

The previous section summarized the general sources of uncertainty in surface-water and groundwater modeling. This section identifies the sources of uncertainty specific to the CVM. Each source of uncertainty includes a brief description of how the model values were estimated for use in the 2020 SYR. Refer to the 2020 SYR Report for a more detailed description of each model input.

3.1 Historical Data

The following subsections describe the historical data sets that were collected or developed for use in the CVM, not including any historical data used to develop model parameters.

3.1.1 Precipitation

Precipitation is the primary source of water for the 2020 CVM watershed. Estimates of precipitation over the 2020 CVM model domain were developed from precipitation stations operated and/or reported by the Los Angeles, San Bernardino, and Riverside County Flood Control Districts, NOAA, and others, and gridded precipitation data products produced by the PRISM Climate Group and NOAA. The monthly gridded precipitation estimates from the PRISM Climate Group were used to inform the spatial distribution of daily precipitation developed from precipitation stations for the period prior to the availability of gridded daily precipitation estimates from NEXRAD. NEXRAD estimates of daily precipitation were used starting in 2002.

3.1.2 Stream Discharge

Daily discharge estimates were obtained from the USGS through the USGS National Water Information System for the streams and channels tributary to and including the Santa Ana River. These discharge data were used in calibration of multiple parts of the CVM, including mountain-front runoff from the San Gabriel Mountains (the HSPF model) and the rest of the Chino Basin watershed tributary to Prado Dam (the R4 model).

3.1.3 Pumping

With one exception, groundwater pumping estimates were obtained from all pumpers through the Chino Basin and Six Basins Watermasters, the City of Corona, and the Cucamonga Valley Water District. The exception is overlying agricultural pumping in the Chino Basin which was estimated with the R4 model for the period 1978 through 2004.

3.1.4 Managed Aquifer Recharge

With one exception, estimates of Managed Aquifer Recharge (MAR) in the 2020 CVM domain were obtained from the entities that conduct recharge operations. The exception is estimates of stormwater captured at the major stormwater detention and recharge facilities in the Chino Basin which was estimated with the R4 model for the period 1978 through 2004. Starting in 2005, IEUA prepared estimates of stormwater captured at these facilities.

3.1.5 Wastewater Discharges

Wastewater discharge to stream channels in the 2020 CVM watershed. Data was obtained from the California Integrated Water Quality System, annual reports of the Santa Ana River Watermaster, the Cities of Corona and Riverside, IEUA, and San Bernardino.

3.1.6 Groundwater Levels

Groundwater level measurements were obtained from the Chino Basin and Six Basins Watermasters the Cities of Corona and Riverside, Cucamonga Valley Water District, the USGS, and the West Valley Water District.

3.1.7 Land Use

Historical land use datasets were acquired from the Southern California Association of Governments (SCAG), the DWR, and San Bernardino County. These land use datasets were available for specific years, and historical data before 1990 have gaps of six years or more between datasets. The R4 surface water model was run to simulate DIPAW and stormwater recharge (when data were unavailable) for each of these land use years, and the values were linearly interpolated between land use years.

3.1.8 Potential ET

ET_0 estimates for the 2020 CVM watershed were obtained from the California Irrigation Management Information System (CIMIS) stations located in Pomona and Riverside. The spatial distribution of daily ET_0 across the 2020 CVM watershed was estimated from the Pomona and Riverside CIMIS station ET_0 estimates using a spatial-temperature interpolation algorithm. For the period prior to these CIMIS stations becoming active, ET_0 was estimated by regression relationships developed at these stations with evaporation at Puddingstone reservoir.

3.1.9 Evaporation

Pan evaporation data from a Thompson-class evaporation pan, located at Puddingstone reservoir, was used to estimate evaporation losses from free water surface from surface water impounded in flood control and conservation basins and streamflow in channels.

3.1.10 Subsurface Inflow from Adjacent Groundwater Basins

Subsurface inflow from the Riverside Basin to the Chino Basin through the so-called Bloomington Divide area was set as a time-variant specified head boundary for the calibration period. The hydraulic conductivity of Layers 1, 3 and 5 adjacent to this boundary and the subsurface inflow from the Riverside Basin were estimated in calibration using the observed groundwater levels located in the Riverside Basin near the boundary.

Subsurface inflow from the Rialto Basin that occurs across the Rialto-Colton Fault was assumed to be the same value estimated in the calibration of the 2013 Chino Basin Model (WEI, 2015). The flux across the Rialto Fault is assumed to be either a constant inflow rate to the Chino Basin or a no-flow boundary depending on the geology along the fault. The range of subsurface inflow from the Arlington Basin to the Temescal Basin was estimated based on the Arlington Basin Model (WEI, 2009).

3.1.11 Unmanaged and Unintentional Recharge

Maliva (2019) defines unmanaged and unintentional recharge as "recharge incidental to other human activities. Unmanaged and unintentional urban recharge includes leakage from water and wastewater mains, discharges from on-site sewage systems, recharge from stormwater management infrastructure, and return flows from the irrigation of parks, lawns, and other vegetated areas." The recharge estimates from on-site sewage systems and irrigation return flows are described below. The leakage from water and wastewater mains are not explicitly accounted for in the groundwater model for multiple reasons: 1) the inability to quantify the magnitude and geographic distribution of these losses and the proportion of losses that result in recharge, and 2) the likely small magnitude of these losses compared to the other recharge components in the Chino Basin. Recharge from stormwater management infrastructure (i.e., Municipal Separate Storm Sewer Systems) beyond the managed recharge facilities is minor (WEI, 2018a) and not explicitly accounted for in the CVM.

3.1.12 Septic Tank Discharge

Data for parcels with septic tanks were collected for the entire CVM model domain. The septic tank parcel data were overlaid on the groundwater model, and the numbers of septic tank parcels within each model cell were determined. Various leakage rates from septic tanks were applied to account for the groundwater recharge flux of each model cell with septic tanks. These rates were based on observed in wastewater inflows to nearby wastewater treatment plants.

3.1.13 Applied Water

The initial estimate of applied water for urban areas was estimated from reports prepared by the IEUA. Final estimates of applied water for urban irrigation were developed by calibrating the R4 model and extending the calibration results to non-IEUA areas in the Chino Basin. Estimates of DIPAW for agricultural, native, and undeveloped areas (land in transition from vacant and agricultural uses to urban uses) were made with the R4 model using historical information on vegetation type and associated root zone depth, soil type, permeable area, irrigable area, evapotranspiration, and precipitation.

3.2 Model Parameters

The following subsections describe the data sets and processes used to develop the model parameters for the CVM.

3.2.1 Hydraulic Conductivity, Specific Storage, and Specific Yield

The following procedure was used to estimate horizontal hydraulic conductivity, vertical hydraulic conductivity, specific storage, and specific yield in the groundwater model. First, data collected from multiple well boreholes was used to estimate the aquifer-system properties at the well locations. The Kriging method was used to spatially interpolate the estimates across the model domain. The model domain was then subdivided into several parameter zones based on an estimate of logical depositional environments. Each parameter zone was assigned a scaling factor which was adjusted during the model calibration process. The final calculated parameter value for any model cell (by model layer) was the product of the adjusted scaling factor and the initial hydraulic parameter value.

3.2.2 Hydraulic Characteristics of Faults

The faults that separate the Chino Basin, Cucamonga and Six Basins as well as internal faults and barriers within these basins, were simulated as horizontal flow barriers with the MODFLOW Horizontal-Flow Barrier (HFB) package. The estimated hydraulic conductivity values for these barriers were adjusted through model calibration. The sensitivity analysis conducted during calibration of the CVM indicated that the hydraulic characteristics of several faults are sensitive in the CVM.

3.2.3 Stream Properties

For use in the surface water simulations, as-built drawings and field surveys from prior investigations were used to develop sub-watershed boundaries, channel and flood control and conservation basin geometry and facility operating schemes. For the groundwater model, the streambed elevations and geometry along creeks and channels were extracted from the 2015 LiDAR data along Santa Ana River with 1-meter resolution (US Army Corps of Engineers, 2015). Other streambed properties (e.g., conductance) were defined based on the streambed characteristics of the Santa Ana River and its tributaries. The stream properties were determined to be insensitive and were not adjusted through model calibration.

3.2.4 Groundwater Evapotranspiration

Groundwater ET was simulated with the MODFLOW Evapotranspiration Segments Package (ETS). This package requires the user to define the spatial extent of the riparian vegetation, the maximum ET rate for each model cell within the spatial extent, and a relationship between ET rate and depth to groundwater. The spatial extent of the riparian vegetation and the maximum ET rates were estimated based on arial photos and the evaporation analysis of the Prado Basin prepared by Merkel (2006). The relationship between the ET rate and depth to groundwater was based on other modeling studies with similar climate and riparian vegetation. The groundwater ET parameters were determined to be insensitive and were not adjusted through model calibration.

3.2.5 Vadose Zone Travel (lag) Time

The HYDRUS-2D model was used to estimate lag time at several boreholes with detailed lithologic descriptions. For the boreholes that were investigated, the primary factor contributing to lag time was vadose zone thickness. These lag times were then generalized throughout the Chino Basin model domain based on vadose thickness and individual lag times were estimated for each model cell. Vadose zone travel (lag) time from the root zone to the water table ranges from about one to four years near the Santa Ana River to over 30 years in the City of Upland area, and typically ranges from 5 to 30 years in other areas. Vadose zone travel (lag) time was not adjusted through model calibration.

3.2.6 Land Use Parameters

Land use parameters (hydrologic soil type, crop coefficient, irrigation efficiency, curve number for impervious area, etc.) were obtained from the Department of Water Resources, Natural Resources Conservation Service (NRCS), San Bernardino County, and the Southern California Association of Governments. Land use type parameters were not adjusted through model calibration.

3.3 Demand and Supply Plan Projections

The following subsections describe the assumptions and data used to develop future projections for water demands and supply plans for the projection scenario of the CVM.

3.3.1 Projected Groundwater Pumping

Watermaster submitted a comprehensive data request to each Appropriative Pool Party and some of the larger Overlying Non-Agricultural Pool pumpers. Watermaster staff reviewed the Parties' responses and followed up for clarification, if necessary. The data provided by the Parties represents the best estimates of their demands and associated water supply plans. Individually and in aggregate, these water demands and associated supply plans were the most reliable planning information available at that time. Watermaster translated the Parties' groundwater pumping projections included in the supply plans based on information regarding well priorities and the timing of groundwater pumping provided by each Appropriative Pool Party.

3.3.2 Projected Managed Artificial Recharge

Projected stormwater recharge in flood control and conservation basins was estimated with the R4 model based on existing and planned 2013 RMPU facilities that are assumed to be fully operational in 2023. Projected recycled water recharge is based on IEUA projections modified in the near term based on recent recharge history. Imported water was assumed to be recharged to meet Watermaster's replenishment obligations only.

3.3.3 Projected Wastewater Discharge

With one exception, the projected wastewater discharges were based on the "Most Likely Discharge" scenario documented in the Santa Ana River Waste Load Allocation Model Update Report (Geoscience, 2020a). These projected discharges were based on estimates provided by the owners of each of the Publicly Owned Treatment Works (POTWs) that discharges wastewater to the Santa Ana River or its tributaries.

3.3.4 Land Use

Land use was assumed to transition from 2018 conditions to "built-out" conditions by 2040. Built-out conditions assumes 2018 land use with vacant and non-urban land uses to converted to land uses shown in the General Plans of the counties and municipalities that overlie the Chino Basin.

3.3.5 Subsurface Inflow from Adjacent Groundwater Basins

Subsurface inflow from the Rialto Basin that occurs across the Rialto-Colton Fault and subsurface inflow from the Arlington Basin to the Temescal Basin are modeled as they were in the calibration period. Groundwater discharges from the Riverside Basin to the Chino Basin through the so-called Bloomington

Divide area was set as a constant specified flow boundary was assumed equal to the average subsurface inflow from the last five years of the calibration period.

3.3.6 Unmanaged and Unintentional Recharge

Future assumptions for unmanaged and unintentional recharge (with the exceptions identified below) are identical to the assumptions used in the historical data.

3.3.7 Septic Tank Discharge

Future locations of septic tank parcels are based on the land use planning data. The leakage rates from septic systems are assumed identical to the leakage rates assumed at the end of the calibration period.

3.3.8 Applied Water

Future assumptions for outdoor applied water are derived from the future water demand and water supply estimates discussed above and the irrigation assumptions for outdoor water use developed in model calibration. Given the uncertainties of the implementation and effects of the "Making Conservation a California Way of Life" legislation, any prescribed changes due to this legislation were not considered in the 2020 SYR projection scenario.

3.3.9 Projected Replenishment Obligation

Projected future replenishment obligations are based on current and projected Safe Yield and assumptions of the transfer activity among the Parties. This process is described in detail in the 2020 SYR Report.

3.3.10 Future Management Programs

Beyond recalculation of the Safe Yield, the CVM is used to support other management goals pursuant to the Program Elements of the Chino Basin Optimum Basin Management Plan. These management goals include maximizing recharge in the basin, managing land subsidence, ensuring the management of water quality, and supporting riparian habitat. To address these management goals, future management actions may be required that would alter the projected supplies and demands (e.g., reducing pumping to mitigate subsidence).

3.4 Projected Climate Impacts on Land Surface Processes

The DWR (2018) climate change datasets in the form of change factors of precipitation, ET_0, and surface runoff for 2030 and 2070 were used to model climate change in the 2020 Safe Yield Recalculation. The impact of new conservation legislation was not included in the 2020 Safe Yield Recalculation.

4.0 POTENTIAL APPROACHES FOR CHARACTERIZING AND ADDRESSING UNCERTAINTY

This section presents a summary of the tools and approaches for characterizing model-parameter and predictive uncertainties that may exist in groundwater models, including errors introduced by model-design and process-simulation assumptions, incomplete knowledge of model parameters, and contributions to predictive uncertainty from estimated future system stresses, such as water demands, supply plans, policies, and climate (Doherty, Hunt, and Tonkin, 2011; Hunt and Welter, 2010).

Approaches to characterize uncertainty in simulation models range in complexity and include the following categories:

1. **Deterministic:** A deterministic approach assumes and simulates one possible future. For example, the 2020 CVM that was used to calculate Safe Yield assumed a single physical groundwater system realization (aquifer parameter distribution) and a future scenario that was developed based on the climate change factors provided by the DWR and the water suppliers' best estimates of the future water demand and supply plans.
2. **Robust Decision Making (RDM):** In this approach, numerous model scenarios are run with various input datasets to determine the possible outcomes against a wide range of plausible futures. The input datasets may include one or more of the following:
   - Alternate physical groundwater system realizations that meet the calibration criteria.
   - Alternate future climate projections (e.g., precipitation and ET_0 projections based on climate models).
   - Alternate water demand and supply plans based on various assumptions of future population, water management policy implementation, and expected behavior of individual pumpers.
   - Predetermined management actions or anticipated projects affecting the stresses in the model (e.g., additional wells or recharge basins). Most of the approved GSPs and Alternative GSPs simulate the groundwater responses to scenarios including management actions pursuant to the SGMA (e.g., Dudek, 2019; Santa Cruz Mid-County Groundwater Agency, 2019; MWH, 2016).
3. **Dynamic Planning:** In a dynamic planning framework, management actions are triggered by the state of the system, which can be a single variable or a combination of variables. For example, well field pumping can be dynamically adjusted based on the simulated groundwater level to prevent the groundwater level from dropping below a threshold level. In another example, stream flow diversion can be dynamically adjusted to ensure a minimum stream flow is maintained. Dynamic planning frameworks require a thorough understanding of potential triggers and actions which often assume centralized planning, where a single decision-maker determines management actions, which is often unrealistic in a real-world planning process (Giuliani et al., 2015). A dynamic planning framework may require iterative input from different sets of stakeholders (Quinn et al., 2017; Wu et al., 2016) and could be revised to represent a decentralized process in which multiple agents optimize for their individual benefits (Jenkins et al., 2017).

The current practice of periodic recalculations of the Safe Yield that involves periodic methodology review and stakeholder involvement is an example of a dynamic planning framework. However, the current deterministic approach of using a single calibration realization and projection scenario does not allow for an assessment of the uncertainties in model projections. The RDM approach is recommended for the development of groundwater models for SGMA compliance (Moran, 2016) without introducing additional complexities and potential uncertainties that may be present in a dynamic planning framework. Therefore, the recommended approaches in this technical memorandum are based on RDM principles.

4.1 Historical Data

Historical data includes records of precipitation, stream discharge, pumping, and other data sets described in Section 3.1. While there is some uncertainty in the historical data, it is our professional judgement that an uncertainty analysis of the historical data would be of limited value to the calibration of the model and the calculation of the Safe Yield. The 40 years of measured data used for calibration of the 2020 CVM was collected by numerous entities and it is appropriate to assume that these measurements have random errors overall. Therefore, for the uncertainty analysis of the calibration parameters, the uncertainty in observed data will not be addressed. This approach was agreed upon by the peer review committee at its October 26, 2021 meeting.

4.2 Model Parameters

The 2020 CVM (WEI, 2020) consists of HSPF and R4 surface-water models and a groundwater model based on MODFLOW-NWT (Niswonger et al., 2011). The surface-water models were calibrated manually. R4 was used to estimate DIPAW at the root zone, to estimate stormwater runoff and stormwater recharge, and to simulate the routing of water through lined and unlined channels across the model domain. The estimated DIPAW was used as groundwater recharge to the groundwater model by considering storage and travel time through the vadose zone. The estimated runoff values were diverted to applicable stream reaches. The routed water was sent to recharge basins or stream reaches. The groundwater model was calibrated by conducting a sensitivity analysis of model parameters using the parameter estimation code PEST (Doherty, 2018) to adjust sensitive parameters to improve the model representation of the groundwater system by minimizing the differences between the historical and the model-calculated groundwater level elevations and discharge of the Santa Ana River at Prado Dam. A residual analysis of the observed versus simulated data was conducted to evaluate and characterize model error.

The problem of non-uniqueness needs to be addressed because parameter and predictive uncertainty is unavoidable. Justification for the use of a model in environmental management must not rest on an assumption that the model’s predictions will be correct. Rather, justification for its use must rest on the premises that its use (i) enables predictive error and/or uncertainty to be quantified and (ii) provides a computational framework for reducing this predictive error and/or uncertainty to an acceptable level, given the information that is available. As such, by quantifying the uncertainty associated with predictions of future hydrologic system behavior, associated risk can inform the decision-making process (Doherty, Hunt, and Tonkin, 2011).

4.2.1 Approaches to Characterizing Uncertainty in Model Parameters

This section presents three selected methods to quantify predictive uncertainties and discusses each method’s associated computational framework. The focus of each of the methods is to efficiently generate a sufficient number of calibrated groundwater system realizations (calibrated realizations) – each realization comprises a set of model parameters that meet the model calibration criteria. Once this is done, an ensemble of projection realizations can be generated by replacing the parameters of the projection model with the parameters of the calibrated realizations. The result of the ensemble of projection realizations is an ensemble of probable outcomes that can be used to determine the central tendency of projected Safe Yield and to quantify the uncertainty of the projected Safe Yield due to uncertainties in model parameters.

4.2.1.1 Generalized Likelihood Uncertainty Estimation (GLUE)

GLUE (Beven and Binley, 1992) is a statistical method used in hydrology for quantifying the uncertainty of model predictions. GLUE assumes the concept of equifinality of models, parameters, and variables. Equifinality originates from the imperfect knowledge of the system under consideration, and many sets of models, parameters, and variables may therefore be considered equal or almost equal simulators of the system. The GLUE methodology can be implemented in the following steps.

1. Select a group of model parameters with the highest relative sensitivity and define the distribution function of each selected parameter.
2. Conduct a Monte Carlo (Eckhardt, 1987; Tarantola, 2005) sampling analysis in the following steps:
    a. Randomly pick a set of parameters within their respective bounds.
    b. Modify the calibration model with the random set of parameters.
    c. Run the modified model and check for the calibration criteria. If the calibration criteria are met, save the set of parameters as a calibrated parameter realization.
    d. Repeat steps (a) to (c) until a defined number of realizations is reached.
3. Generate projection realizations. A projection realization is based on the parameters of a calibrated parameter realization and incorporates climate, hydrology, and supply/demand projections.
4. Conduct simulation runs of the projection realizations. Develop recommendations based on the simulation results of the realizations.

White (2018) applied the GLUE method on a synthetic model (Freberg, 1988) with 100,000 realizations of five model parameters (i.e., hydraulic conductivity, historical recharge, future recharge, historical pumping rate multiplier, and future pumping rate multiplier) to quantify the efficacy of the Monte Carlo sampling analysis and to compare it with PESTPP-IES (see below). The Monte Carlo sampling analysis identified 275 calibrated realizations (an acceptance rate of 0.275 percent) that met a predefined calibration criterion. Had this method been applied to the 2020 CVM, which took four hours to complete a model run, it would take 45 years to obtain 275 realizations for the same acceptance rate. Due to the low acceptance rate, this method is often not practical for complex models with a long run time.

4.2.1.2 Null-Space Monte Carlo (NSMC)

NSMC (Tonkin and Doherty, 2009) is a method for generating calibrated realizations. Instead of creating a single calibrated realization, NSMC can be used to create multiple calibrated realizations. The NSMC methodology can be implemented in the following steps (Doherty, Hunt, and Tonkin, 2011).

1. Prior to implementation of a NSMC analysis, it is assumed that a model has been calibrated, a set of calibrated model parameters is available, and the distribution functions of each parameter is defined.
2. Conduct a NSMC sampling analysis in the following steps with the help of multiple programs (RANDPAR, FIELDGEN, PPSAMP, PNULPAR, FAC2REAL, and TWOARRAY) included in the PEST Groundwater Data Utility (Watermark Numerical Computing, 2020).
    a. Randomly pick a set of parameters within their respective bounds.
    b. The calibrated parameters are subtracted from the stochastically generated parameters.

   c. The result of step (b) is projected onto the calibration null space.
   d. The solution-space component of the stochastically generated parameters is replaced by the parameter field arising from the calibration.
   e. Recalibrate the model and save the set of parameters as a calibrated parameter realization. Ideally, because null-space parameter components do not appreciably affect model outputs that correspond to elements of the calibration dataset, the null-space processing of the optimal parameter set in step (d) should result in a calibrated model. In practice, however, the null-space-processed parameters commonly result in a slightly de-calibrated model. Recalibration of such a model normally requires only a fraction of the number of model runs per iteration as there are adjustable parameters.
   f. Repeat steps (a) to (e) until a desired number of calibrated parameter realizations is reached.
3. Generate projection realizations. A projection realization is based on the parameters of a calibrated parameter realization and incorporates climate, hydrology, and supply/demand projections.
4. Conduct simulation runs of the projection realizations. Develop recommendations based on the simulation results of the realizations.

Overall, the NSMC sampling analysis involves many computational steps that require specific programs and input parameters. A conceptual example for implementing the second level of parameterization is given in Part B of the Groundwater Data Utility (Watermark Numerical Computing, 2020).

4.2.1.3 Iterative Ensemble Smoother (iES)

Most algorithms for model parameter estimation (PE) and uncertainty quantification (UQ) are computationally constrained by number of adjustable parameters. Because of this constraint, assumptions must be employed to reduce the number of parameters, which is a form of model simplification. This simplification can lead to model error phenomena such as parameter compensation and undetectable forecast bias (White, 2018; Doherty and Christensen, 2011).

To relax or eliminate the computational bounds induced by the number of parameters, iterative ensemble smoothers (iES) have emerged as a class of algorithms for PE and UQ. Chen and Oliver (2012, 2013) introduced an efficient iES formulation, which was implemented by White (2018) and White et al. (2020) in the open-source code PESTPP-IES. Based on the nature of the iES algorithm, the number of model runs per estimation iteration depends on the number of desired calibrated groundwater system realizations, and does not depend on the number of adjustable parameters. Additionally, the iES algorithm yields an ensemble of the calibrated parameter realizations that can be used to quantify uncertainty in forecasts of interest.

PESTPP-IES can be applied in the following steps.

1. Construct a model and prepare for parameter estimation according to the input instructions of PEST and PESTPP-IES, including the pilot points as well as variograms and covariance matrices of adjustable model parameters. Covariance matrices can be generated based on the variograms of adjustable parameters.
2. Run PESTPP-IES to generate the desired number of calibrated parameter realizations. In order to achieve a good fit between model outputs and the calibration dataset, the number of the desired calibrated parameter realizations (and hence the number of model runs) must

be greater than the dimensionality of the solution space of the inverse problem. The dimensionality of the solution space often must be guessed. An ensemble size of a few hundred (and often less) is suitable for most occasions (Doherty, 2021).

3. Generate projection realizations. A projection realization is based on the parameters of a calibrated parameter realization and incorporates climate, hydrology, and supply/demand projections.
4. Conduct simulation runs of the projection realizations. Develop recommendations based on the simulation results of the realizations.

In comparison with the NSMC method, the iES-based solution is relatively straightforward. The required utility programs for preparing required input to data to PESTPP-IES are readily available as well.

4.2.2 Recommendation

All methods described above can be used to address parameter uncertainties. However, a comparison of the major criteria shown in Table 2 suggests that the iES is the most favorable method due to the computation time being independent of the number of adjustable parameters, which results in a relatively lower computing cost. The iES method and its software implementation PESTPP-IES are recommended to be used for quantifying parameterization-related uncertainties. Attachment A documents the use of a synthetic model to illustrate the detailed steps to generate calibrated parameter realizations with PESTPP-IES and other utility programs.

Table 2. Comparison of methods to quantify predictive uncertainties

Criteria	GLUE	NSMC	IES
Simplicity of the Method	Simple	Complex	Moderate
Computing Cost (in terms of the number of required model runs)	High (due to low acceptance rate)	Moderate (due to the requirement of recalibration of each parameter set)	Low
Does the computing cost grow with the number of adjustable parameters?	Yes	Yes	No
Ability to incorporate heterogeneity in calibrated realizations	Yes (at a very high computing cost)	Yes (at a very high computing cost)	Yes

4.3 Demand and Supply Plan Projections

Water demand and supply plans depend on various assumption of future conditions, such as population, climate, and regulatory requirements. The uncertainty associated with water demand and supply plans should be quantified because water demand and supply plans include projections of pumping, recharge, and storage which can affect groundwater levels and the net recharge of the Chino Basin.

4.3.1 Approaches to Characterizing Uncertainty in Demand and Supply Plan Projections

Several water resource planning studies in the Santa Ana River watershed and North America have employed RDM or similar approaches to address uncertainties in future water demands and supply plans (USBR, 2012; Dennehy, 2021; Miro et al., 2021; Valley Water, 2022). The planning studies that employ RDM generally have the objective of evaluating uncertainties in future conditions to inform management or planning decisions. The amount of detail applied to develop scenarios using RDM is not prescribed and depends on the available data to characterize external drivers, management schema, and planning objectives (Groves et al., 2019).

San Bernardino Valley Municipal Water District (Valley District) recently employed RDM in their water resources planning (Miro et al., 2021), which included development of four scenarios of future demands and nine scenarios of future imported water supply. The demand futures were developed with the Valley District's retail agencies to understand the drivers in water demand and the uncertainties in projecting changes in water demand. The range in potential future imported water supplies were derived from the Metropolitan Water District of Southern California's simulated operational scenarios of the State Water Project, the imported water supply in the region.

4.3.2 Recommendation

The current Safe Yield Reset methodology would be improved by shifting from a deterministic approach to an RDM approach involving multiple discrete demand and supply plan scenarios. To quantify the uncertainty in demands and supply plans in the Chino Basin and develop demand and supply plan scenarios, a method similar to what Valley District employed to implement the RDM approach (Miro, et al., 2018; Miro, et al., 2021) is recommended. The proposed method to execute this approach includes the following:

1. Develop a list of the drivers of changes to future water demands and supplies. Examples of these drivers include population growth, land use, policies (e.g., conservation mandates), and climate change. Conduct one to three workshops with the Parties and wholesale agencies that serve the Chino Basin to ensure that the most significant drivers are considered.
2. Use the drivers identified in step 1 above to develop demand and supply plan scenarios. These scenarios will include assumptions of each driver and its effect on future demands and water supply plans.
3. Select a subset of the demand and supply scenarios developed in step 2 that will be incorporated into the projection realizations.
4. Develop quantitative water supply plans for the selected demand and supply scenarios. This will rely on a review of relevant planning information (e.g., Urban Water Management Plans, regional water resources planning studies [Groves and Syme, 2022], and data on cultural conditions collected pursuant to the 2017 Court Order) and workshops with the Parties and wholesale agencies. This effort will leverage existing planning studies to define the scenarios and will not include the development of any new planning studies (e.g., Oxnard, 2017; Miro, et al., 2018; Valley Water, 2022). Conduct at least two workshops with the Parties and wholesale agencies to refine and iterate the water supply plans.
5. Translate the demand and supply scenarios and water supply plans into model inputs (e.g., groundwater pumping, outdoor urban water use, managed recharge, imported water, others) and integrate into projection realizations.

We recommend the development of up to six scenarios to capture plausible combinations of drivers (e.g., population growth, water conservation, and restriction of imported water) and their effect on water demand and supply plans.

4.4 Climate Projections

As described in Section 2.1.4, the climate directly and indirectly impacts the groundwater system through recharge and changes in groundwater use. To incorporate the climate impacts in a groundwater model projection, future precipitation and ET_0 values must be estimated. In the 2020 CVM, future precipitation and ET_0 values were obtained by adjusting the historical records by the DWR Change Factors (DWR, 2018). Since the DWR Change Factors were derived based on the ensemble average of 20 selected model runs from CIMP5, the 2020 CVM implemented a deterministic climate scenario representing the projected central tendency of future climate. In this approach, the uncertainty in the projected Safe Yield due to individual climate projections could not be characterized.

To overcome this limitation, relevant literature was reviewed to explore the feasibility of estimating future precipitation and ET_0 values based on the available climate model datasets. The following sections document the findings and recommendations from the literature review.

4.4.1 Approaches to Characterizing Uncertainty due to Climate Change

This section provides an overview of the state of global climate model research and the available datasets from the climate models.

4.4.1.1 State of Global Climate Models (GCMs)

GCMs are numerical models and are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. Many GCMs were developed in the past decades by research institutes across the world. GCMs vary in their capabilities, including algorithms, grid resolutions, and simulated earth system processes. Global climate research efforts are coordinated by the Intergovernmental Panel on Climate Change (IPCC) through a series of the Coupled Model Intercomparison Projects (CMIPs). In each iteration of the CMIPs, prescribed assumptions of future climate forcing factors and boundary conditions are implemented by various GCMs. As a result of variations in GCMs, their projected outcomes are different despite having the same prescribed forcing assumptions and boundary conditions.

The change factors provided by DWR are based on the GCMs from the fifth iteration of CMIP (CMIP5) that was completed in 2012 (Taylor and others, 2012). The sixth iteration of CMIP (CMIP6) (PCMDI, 2021) is the most recent update. The models included in CMIP6 improve the representation of atmospheric and biogeochemical processes (e.g., cloud formation), have denser grids, and are better able to simulate historical conditions than the CMIP5 models (Thorarinsdottir et al., 2020). Furthermore, there are more future scenarios available for CMIP6 that can be chosen to couple with the water demand and supply plan scenarios.

4.4.1.2 Downscaled Climate Model Datasets

All GCMs of each CMIP are required to produce a set of simulation results, including time series of precipitation and near-surface temperature at each model grid cell. Raw GCM output, however, is not always adequate to be used directly in groundwater and surface-water models. Two primary impediments to impacts studies are the coarse spatial scales represented by the GCM (grid cells are typically between 150 and 400 miles long on the ground surface), and the GCM raw output contain biases relative to observational data, which preclude its direct use. A variety of downscaling methods can be used to process and refine GCM output with the aim of producing output more suitable for planning models. The refined output aims to address the limitations of coarse resolution and/or regional biases in the GCM output.

Downscaling methods can be divided into two broad categories: dynamical and statistical. Dynamical downscaling refers to the use of high-resolution regional simulations to dynamically interpolate the effects of large-scale climate processes to regional or local scales of interest. Statistical downscaling encompasses the use of various statistics-based techniques to determine relationships between large-scale climate patterns resolved by global climate models and observed local climate responses. These relationships are applied to GCM results to transform climate model outputs into statistically refined products. The available downscaled climate model datasets are summarized below.

Statistical Downscaled Datasets

- NASA Earth Exchange (NEX) Downscaled Climate Projections (NEX-DCP30)
  - Description: This dataset comprises downscaled climate scenarios for the conterminous United States that are derived from the GCM runs conducted under CMIP5 and across the four greenhouse gas emissions scenarios known as Representative Concentration Pathways (RCPs). Each of the climate projections includes monthly averaged maximum temperature, minimum temperature, and precipitation at a resolution of 800 meters for the periods from 1950 through 2005 (Retrospective Run) and from 2006 to 2099 (Projection Run).
  - Website: https://ds.nccs.nasa.gov/thredds/catalog/bypass/NEX-CP30/bcsd/catalog.html
  - Data access: https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-dcp30
- NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6)
  - Description: This dataset comprises global downscaled climate scenarios derived from the GCM runs conducted under CMIP6 and across two of the four "Tier 1" greenhouse gas emissions scenarios known as Shared Socioeconomic Pathways (SSPs). Each of the climate projections includes daily averaged maximum temperature, minimum temperature, and precipitation at a resolution of 0.25 degrees (approximately 17.5 miles at equator) for the periods from 1950 through 2014 (Retrospective Run) and from 2015 to 2100 (Projection Run).
  - Website: https://ds.nccs.nasa.gov/thredds/catalog/AMES/NEX/GDDP-CMIP6/catalog.html
  - Data access: https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6

Dynamical Downscaled Datasets

- CMIP6 Downscaling Using the Weather Research and Forecasting model (WRF-CMIP6).
  - Description: This dataset comprises dynamically downscaled climate scenarios derived from the GCM runs conducted under CMIP6 using the WRF model. Each of the climate projections consists of 37 daily variables including temperature, precipitation, evapotranspiration, wind speed at a resolution of 2 miles (3 km) for the periods from 1980 through 2100.

- Website: https://dept.atmos.ucla.edu/alexhall/downscaling-cmip6
- Data access: https://dept.atmos.ucla.edu/sites/default/files/alexhall/files/aws_tiers_dirstructure_Jan22.pdf

4.4.2 Recommendation

Given the range of improvements in the CMIP6 models and the greater variety of scenarios, using data sets derived from the CMIP6 models is the most defensible approach to apply to the CVM. Two options for applying the CMIP6 datasets to the CVM are using the Change Factors or using the dynamically downscaled datasets. The former is infeasible as CMIP6-based Change Factors are not yet available. The remaining option is to use the dynamically downscaled datasets.

The two available CMIP6-based downscaled datasets are the NEX-GDDP-CMIP6 and WRF-CMIP6 datasets. The statistically downscaled dataset NEX-GDDP-CMIP6 is only available at a spatial resolution of 0.25 degrees, which is not sufficient to capture the topographic and orographic drivers of precipitation and temperature patters across the Chino Valley watershed. The dynamically downscaled dataset WRF-CMIP6 is available at a 3 km resolution and is appropriate to apply to the CVM. The development of the WRF-CMIP6 datasets is an ongoing project. Currently, the downscaled datasets of nine GCM scenarios are available, and it is expected that additional datasets for other GCM scenarios will be available when the projections for the forthcoming Safe Yield recalculation will be developed.[9] Therefore, the WRF-CMIP6 datasets are recommended to be used in the updated Safe Yield calculation methodology to account for the effects of future climate variations.

The following method is proposed to implement the dynamically downscaled CMIP6 data into the CVM.

1. Review and select a subset of the available dynamically downscaled datasets (i.e., combinations of GCMs and scenarios). The selected subset should be representative of plausible future patterns of mean precipitation, ET_0, and temperature of the CVM watershed.
2. Review and select representative future cultural conditions consistent with the water demand and supply plan scenarios. This includes a combination of future land use and applied water patterns. As the Chino Basin is expected to be built out by 2040, and the land use change from agricultural to urban uses is not expected to significantly affect DIPAW, it is practical to assume a single future land use to combine with the selected range of applied water patterns to characterize representative future cultural conditions.
3. Incorporate the chosen combinations of climate datasets and cultural conditions into the CVM:
   - Execute the HSPF and R4 models are executed with the land use data, precipitation, and ET_0 datasets from the climate projection. The results of the HSPF and R4 simulation (including DIPAW, stormwater discharge to streams, and stormwater recharge) will be used as input data of the MODFLOW model of CVM.
   - Develop SAR discharges from the upper SAR watershed at Riverside Narrows based on regional model results (e.g., Geoscience, 2020b) which should include the climate projection as part of the model input. The estimated SAR discharges at Riverside Narrows will be used as input data to the MODFLOW model of CVM.

[9] Correspondence with Stefan Rahimi-Esfarjani, March 31, 2022

5.0 RECOMMENDED PROCESS FOR CALCULATING SAFE YIELD

Section 4.0 outlined the potential approaches and recommended methods for addressing uncertainty in the model parameterization, future water demands and supply plans, and future climate scenarios. This section includes recommendations and considerations for interpreting the model ensemble, the proposed updated Safe Yield Reset methodology, and the anticipated costs of implementing the proposed methodology.

5.1 Recommended Implementation of Ensemble Approach

Implementing the recommended methods in Section 4.0 will result in the development of multiple projection realizations, which are unique combinations of calibrated model realizations, future demands and water supply plans, and climate scenarios. The number of projection realizations is the product of the number of calibrated model realizations, demand and supply plan scenarios, and climate scenarios. For example, a total of 40 calibrated model realizations, three demand and supply plan scenarios, and five climate scenarios would result in 40 x 3 x 5 = 600 projection realizations. If the simulation of each realization takes a day to complete, a single computer CPU will need 600 days to simulate the ensemble of 600 realizations. Simulating several hundred projection realizations will require significant computing power, which can be acquired from commercial cloud computing services. For example, Amazon Web Services (AWS) currently charges a monthly cost of $94 for a 4-CPU-WorkSpace that can simulate three realizations simultaneously (1 CPU is needed for the operating system). A total number of 40 4-CPU-WorkSpaces will be needed to complete the simulation of 600 realizations in five days, or 1,200 realizations in ten days. The total monthly cost for 40 4-CPU-WorkSpaces will be $3,760. It is anticipated that three to six months of the computing services will be needed.

5.1.1 Simulation Process and Results

Since a projection realization can produce about 50 Gigabytes of simulation results, it is impractical to store complete model outputs for several hundred to thousands of simulations. Therefore, an automated process will need to be developed to simulate all realizations and to extract/post-process only the model results necessary to quantify net recharge, potential Material Physical Injury (MPI), and the state of hydraulic control. After the simulation of each projection realization, the time series of annual net recharge will be calculated, the potential MPI will be assessed, and the state of hydraulic control will be determined based on the same approach that has been implemented in prior Chino Basin studies (WEI, 2018b; WEI, 2020; WY, 2021).

5.1.2 Interpreting the Ensemble to Calculate the Safe Yield

The results of the proposed simulation process will include the following information for each projection realization:

- Time series of annual net recharge for the simulation period
- Time series of the state of potential MPI, including the potential new land subsidence and the state of pumping sustainability
- Time series of the state of hydraulic control (i.e., groundwater discharge from the Chino-North Groundwater Management Zone to the Prado Basin Management Zone. Hydraulic control is maintained if groundwater discharge is less than the de minimum threshold of 1,000 afy)

Figure 1 shows hypothetical time series of calculated annual net recharge values. The solid blue line represents the ensemble mean annual net recharge, and the shaded blue band indicates the spread in annual net recharge of all the projection realizations.

The Safe Yield of a given period for a projection realization can be calculated as the annual mean net recharge of that realization over a given period (e.g., 2026 to 2035). The Safe Yield for the ensemble of projection realizations can be calculated as the mean of the annual mean net recharge for all projection realizations over the given period. The range and standard deviation of the ensemble Safe Yield can be calculated based on the Safe Yield values of individual projection realizations.

In addition to the Safe Yield values, the probability of MPI and undesirable results can be derived from the time series of the state of hydraulic control and the potential for MPI. The results of the projection realizations can be examined to determine the drivers of violations of hydraulic control or potential MPI (e.g., high groundwater pumping, lower precipitation). Examining the results of the ensemble can inform the planning of potential mitigation actions. To guide the interpretation of the ensemble results, thresholds of significance should be defined to determine the risk of MPI and undesirable results. For example, if less than five percent of the models in the ensemble did not indicate a violation of hydraulic control, then the risk that hydraulic control would be violated at a given Safe Yield could be considered insignificant. The process to determine these significance thresholds should be conducted in advance of the generation of the model ensemble results.

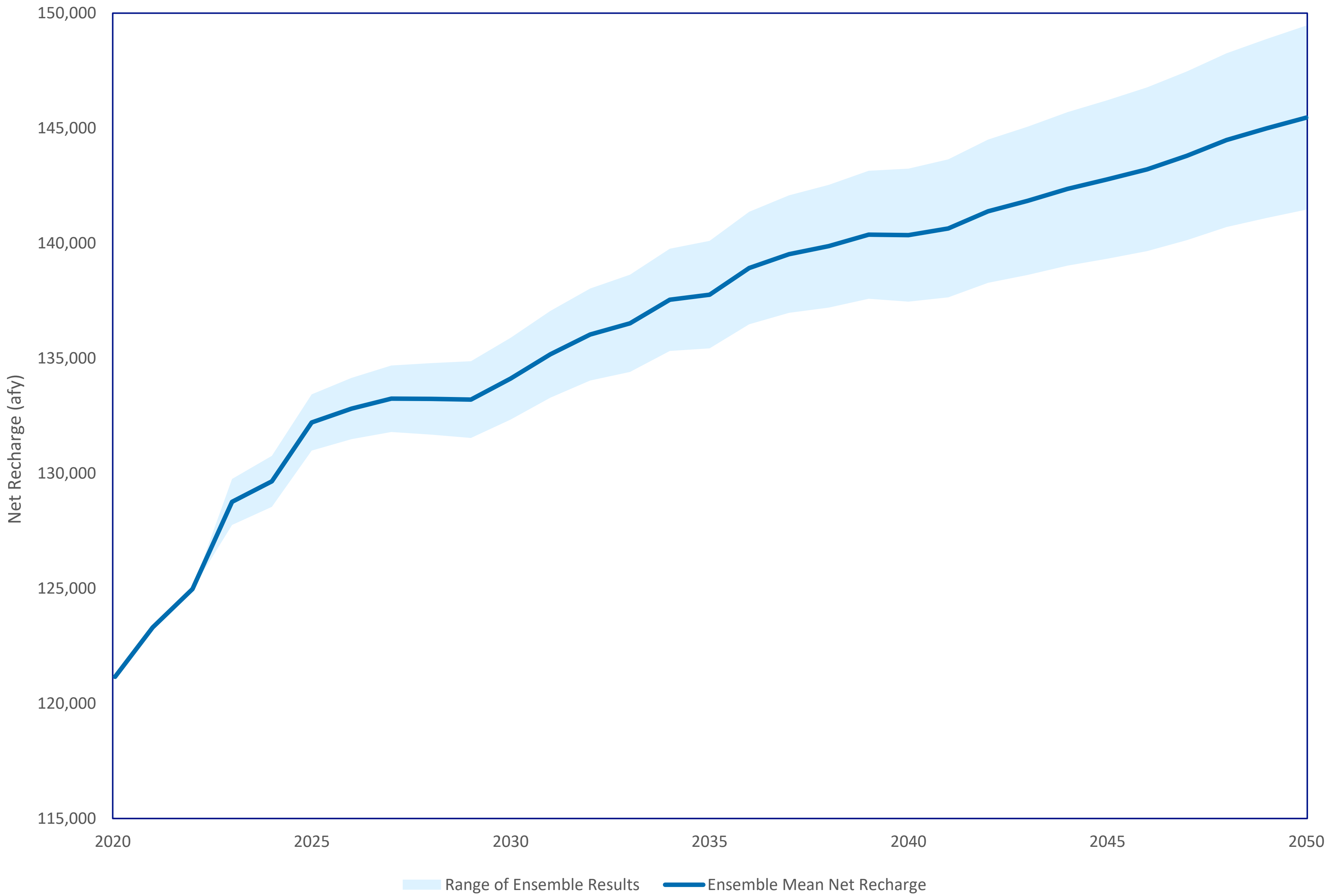
5.2 Proposed Updated Methodology to Calculate the Safe Yield

Based upon the recommended approaches discussed in Section 4.0 and Section 5.1, the following steps comprise the proposed updated Safe Yield Reset methodology:

1. Update model and generate calibrated realizations using the following steps:
   - Update and calibrate the HSPF and R4 models for the historical period (Fiscal Year 1978 to present).
   - Update the MODFLOW flow model for the historical period based on observation data and the results of HSPF and R4.
   - Select adjustable parameters (e.g., horizontal hydraulic conductivity) and prepare input files to incorporate characteristics (such as pilot points, variograms, and covariance matrices) of those parameters for PESTPP-IES.
   - Prepare observation data as calibration targets, such as groundwater level elevation and stream discharge time series.
   - Use PESTPP-IES to estimate model parameters and generate calibrated realizations.
2. Develop future scenarios of demands, water-supply plans, and climate/hydrology using the recommended approaches and methods in Section 4.0.
3. Generate projection realizations. A single projection realization is based on one combination of a calibrated model realization, one future scenario of demands and water supply plans, and one future scenario of climate/hydrology. We propose using up to 600 projection realizations to capture the plausible range of calibrated models and future conditions without resulting in an infeasible computational effort.

DRAFT

Figure 1. Hypothetical Projected Net Recharge Using Ensemble Approach



4. Simulate the ensemble of projection realizations over the planning period and quantify the water budget, net recharge, Safe Yield, assessment of potential MPI, and state of hydraulic control for each projection realization. The model results are stored for each projection realization for the subsequent statistical analyses.
5. Conduct statistical analyses of the model results of the ensemble of projection realizations. The statistical analyses will include:
   - Projection of the annual water budget including the annual net recharge to the basin, including the annual change in storage over the planning period. The planning period should be no less than 50 years to be consistent with the planning period required by SGMA. This is sufficient to evaluate the long-term response of the Chino Basin to the projection realizations to evaluate for MPI and undesirable results.
   - Projection of the Safe Yield over a specified 10-year period (e.g., 2026-2035) as the ensemble mean annual net recharge over the period, including the range and distribution of ensemble results.
   - Statistics of projection scenarios with results indicating MPI. The statistics include the extent of potential MPI as well as details of the projection realization, including type of demand/supply plans, climate/hydrology, or parameter realizations. These statistics will allow for identifying the factors causing MPI.
   - Statistics of projection scenarios with the state of hydraulic control. The statistics include the projection scenarios and their projected time series of groundwater discharge from the Chino-North Groundwater Management Zone to the Prado Basin Management Zone. The hydraulic control is maintained if the groundwater discharge is less than the de minimis threshold of 1,000 acre-ft per year.
6. Evaluate the risk of potential MPI and undesirable results based on the statistics generated in (5). If the risk of MPI and undesirable results is significant (based on a defined threshold), then Watermaster should "identify and implement prudent measures necessary to mitigate [MPI and undesirable results], set the value of Safe Yield to ensure there is no [MPI and undesirable results], or implement a combination of mitigation measures and a changed Safe Yield." Mitigation measures should be guided by an examination of the projection realizations that indicate MPI and/or undesirable results.

5.3 Cost of Implementing Proposed Updated Methodology

In this section, we will provide relative costs of staff time required to implement the proposed updated Safe Yield Reset methodology relative to the current Safe Yield Reset methodology. Table 3 compares the major differences in the steps necessary to implement the current and proposed Safe Yield methodologies.

Table 3. Comparison of Current and Proposed SY Reset Methodologies

Step	Current SY Reset Methodology	Proposed SY Reset Methodology
Calibration of groundwater model	Calibrate groundwater model with parameter zones and PEST to generate single model realization	Calibrate groundwater model using pilot points and PESTPP-IES to generate multiple calibrated model realizations
Incorporation of demand and supply plans in scenario development	Using the current planning data collected from the Parties and other sources to develop a single projection scenario of future demands and supply plans. Minimal stakeholder engagement beyond clarifying the collected data.	Collecting the same data sets as are collected with the current SY Reset methodology. A stakeholder process will be implemented using RDM principles to understand the drivers and potential responses to stresses to aid in the development of multiple plausible projections for demand and supply plans.
Projection realization development	One projection scenario is developed based on a combination of the best estimates of future demands, supply plans, and long-term expected value hydrology adjusted for climate change.	Multiple projection realizations will be developed as unique combinations of calibrated model realizations, future demands and supply plans, and future hydrology and climate.
Evaluation of model results	The projection scenario is evaluated based on whether the projected groundwater pumping *"will cause or threaten to cause 'undesirable results' or 'Material Physical Injury'."*	The method to evaluate model results is similar to the current SY Reset methodology, but the method is automated and applied to the ensemble of projection scenarios. Ensemble statistics are generated to characterize the potential MPI and state of hydraulic control and allow for identification of the drivers that may cause MPI or violations of hydraulic control.
Calculation of Safe Yield based on model results	Safe Yield is calculated as the 10-year average of the net recharge for the single model projection realization.	Safe Yield is calculated as the ensemble mean of the 10-year average net recharge for the ensemble of projection scenarios.

The processes to generate the calibrated realizations and develop and evaluate the projection scenarios can be automated through computer scripts. A planning-level cost estimate for the implementation of the proposed updated Safe Yield Reset methodology has been prepared and is based on (i) an understanding of the cost of implementing the uncertainty analysis to the Chino Basin (based on the process documented in Attachment A), (ii) prior modeling experience in the Chino Basin, and (iii) assumed future billing rates. The total cost of implementing the proposed approach is expected to be between 50 and 100 percent greater than the total cost of the modeling effort of the 2020 SY Recalculation (with escalated rates), which equates to about $1.75 million to $2.3 million over three years. The modeling work is expected to begin in FY 2023 and be completed by the end of FY 2025, broken down in the following:

- FY 2023: Update of hydrogeologic conceptual model and initiate the stakeholder process to prepare the projection scenarios for demands and water-supply plans (current budget is $259,000, representing up to 15 percent of scope)
- FY 2024: Conduct the model calibration and uncertainty analysis, prepare the ensemble of projection scenarios, and begin simulating ensemble of projection scenarios (50 percent of scope; about $900,000 to $1,100,000)

- FY 2025: Complete the simulation and evaluation of the ensemble of projection scenarios, calculate Safe Yield, and prepare report (35 to 40 percent of scope; about $600,000 to $900,000)
- The budgets for FY 2024 and FY 2025 will be refined in future Watermaster budget processes.

6.0 NEXT STEPS AND SCHEDULE

This draft TM will be distributed to the Parties and the peer review committee for review and comment. Watermaster will hold a workshop on May 19, 2022 to review the contents of this TM and solicit feedback from the Parties and the peer review committee. Watermaster requests that comments and feedback on the TM be submitted to Watermaster staff and engineer by June 10, 2022. Watermaster staff and engineer will then prepare an updated draft TM, including written responses to comments, by June 24, 2022. The updated draft TM will be re-distributed to the Parties for review. About two weeks following the distribution of the updated draft TM, Watermaster will hold a second workshop. Depending on the nature of the comments received through the second workshop, the draft TM may be revised again, which would be followed by a third workshop. The TM will be finalized after the final workshop and will include written responses to all written comments.

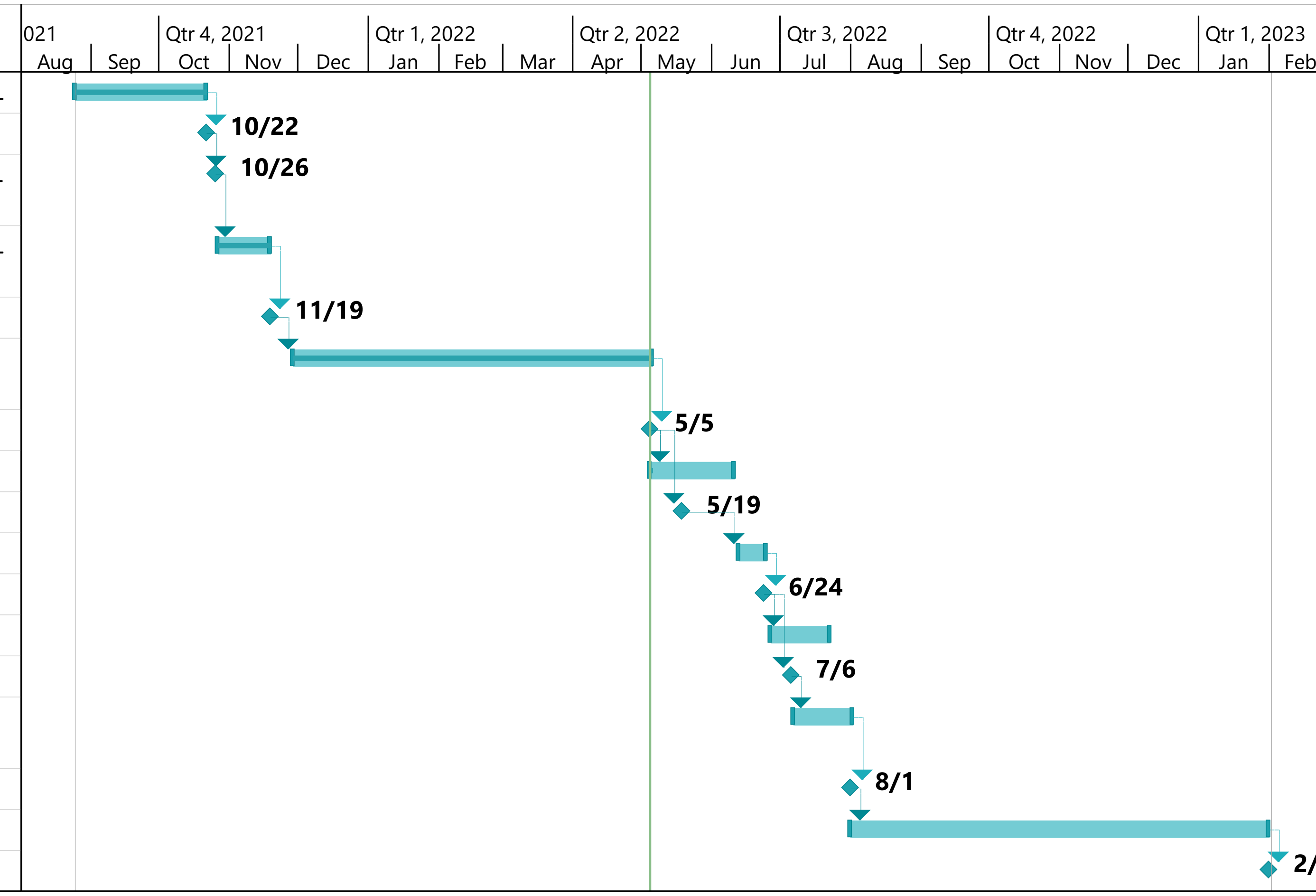
Once finalized, Watermaster staff and engineer will prepare a summary TM that will describe the proposed update Safe Yield Reset methodology which will be suited for submittal to the Court for approval. There is some uncertainty in the nature and length of the Court-approval process, but it is anticipated to take no more than six months.

Figure 2 is a Gantt chart showing the anticipated schedule to develop the updated Safe Yield Reset methodology and gain Court approval of the methodology. The schedule in Figure 2 assumes that two peer review meetings will be sufficient to gather feedback on the proposed methodology. It is anticipated that the Court approval of the updated Safe Yield Reset methodology will occur in early 2023.

Figure 2

DRAFT

ID	Task Number	Task Name	Duration	Start	Finish
1	1.01	Develop initial TM documenting uncertainty in groundwater modeling	42 days	Wed 8/25/21	Thu 10/21/21
2	1.02	Distribute initial TM to Watermaster Parties for review	0 days	Fri 10/22/21	Fri 10/22/21
3	1.03	Peer review meeting of initial TM and addressing uncertainty in CVM and the Safe Yield methodology	0 days	Tue 10/26/21	Tue 10/26/21
4	1.04	Development of supplemental scope and budget, solicit and address questions and comments on supplemental scope and budget	17 days	Wed 10/27/21	Thu 11/18/21
5	1.05	Watermaster Board approval of supplemental scope and budget	0 days	Fri 11/19/21	Fri 11/19/21
6	1.06	Develop proposed updated Safe Yield Reset Methodology and develop first draft TM	114 days	Mon 11/29/21	Thu 5/5/22
7	1.07	Distribute first draft TM to Parties	0 days	Thu 5/5/22	Thu 5/5/22
8	1.08	Party review of first draft TM	27 days	Thu 5/5/22	Fri 6/10/22
9	1.09	Peer review meeting to gather feedback on first draft TM	0 days	Thu 5/19/22	Thu 5/19/22
10	1.10	Watermaster Engineer responds to feedback, develops second draft TM	10 days	Mon 6/13/22	Fri 6/24/22
11	1.11	Distribute second draft TM to Parties	0 days	Fri 6/24/22	Fri 6/24/22
12	1.12	Party review of second draft TM	20 days	Mon 6/27/22	Fri 7/22/22
13	1.13	Peer review meeting to gather feedback on second draft TM	0 days	Wed 7/6/22	Wed 7/6/22
14	1.14	Respond to feedback and develop final TM with updated Safe Yield Reset Methodology	18 days	Thu 7/7/22	Mon 8/1/22
15	1.15	Distribute final TM to Parties and submit to Court	0 days	Mon 8/1/22	Mon 8/1/22
16	1.16	Support Court approval process	132 days	Mon 8/1/22	Tue 1/31/23
17	1.17	Court approves updated Safe Yield Reset Methodology	0 days	Wed 2/1/23	Wed 2/1/23



Project: SYR Method Update
Date: Thu 5/5/22

Task | Milestone/Meeting | Progress

7.0 REFERENCES

Beven, Keith; Binley, Andrew (1992). *The Future of Distributed Models: Model Calibration and Uncertainty Prediction*. Hydrological Processes. 6 (3): 279–298. doi:10.1002/hyp.3360060305. ISSN 0885-6087.

Bruce A., Brown C., Dufour A. (2019). *The Uncertainty and Sensitivity of Long-Term Urban Water Demand Forecasts: How Wrong Can You Be?* American Geophysical Union, Fall Meeting 2019.

California Department of Water Resources (DWR) (2016). Accessed at: *Best Management Practices for the Sustainable Management of Groundwater - Water Budget BMP*

California Department of Water Resources (DWR) (2018). *Resource Guide - DWR-Provided Climate Change Data and Guidance for Use During Groundwater Sustainability Plan Development*.

Chen, Y. and Oliver, D.S. (2012). *Ensemble Randomized Maximum Likelihood Method as an Iterative Ensemble Smoother.* Math. Geosci. 44 (1), 1–26.

Chen, Y., Oliver, D.S. (2013). *Levenberg–Marquardt Forms of The Iterative Ensemble Smoother for Efficient History Matching And Uncertainty Quantification*. Comput. Geosci. 17 (4), 689–703.

Chiang, E. (2022). *User Guide of Processing Modflow 11*. Simcore Software. https://www.simcore.com

Culley, S., Noble, S., Yates, A., Timbs, M., Westra, S., Maier, H. R., Giuliani, M., and Castelletti, A. (2016), *A Bottom-up Approach to Identifying the Maximum Operational Adaptive Capacity of Water Resource Systems To A Changing Climate*, *Water Resources. Res.*, 52, 6751– 6768, doi:10.1002/2015WR018253.

Dennehy, P. (2021). *A Robust Approach for Estimating Future Groundwater Demands in a Dynamic Groundwater Basin*. Presented at the Fourth Annual Western Groundwater Congress, Burbank, CA.

Doherty, J. (2018). *Model-Independent Parameter Estimation User Manual: 7th Edition*. Brisbane, Australia: Water Numerical Computing.

Doherty, J. and Christensen, S., (2011). *Use of Paired Simple and Complex Models To Reduce Predictive Bias and Quantify Uncertainty.* Water Resources. Res. 47 (12).

Doherty, John E., Hunt, Randall J. and Tonkin, Matthew J. (2011) *Approaches to Highly Parameterized Inversion: A Guide to Using PEST for Model-Parameter and Predictive-Uncertainty Analysis.* Groundwater Resources Program Global Change Research & Development Scientific Investigations Report 2010–5211

Doherty, John E. (2019). *Using PESTPP-IES: Continuation of a Groundwater Vistas Tutorial.* https://pesthomepage.org/tutorials. Brisbane, Australia: Water Numerical Computing. Accessed March 2,2022.

Dudek. (2019). *Groundwater Sustainability Plan for the Oxnard Subbasin.* Prepared for the Fox Canyon Groundwater Management Agency, December 2019.

Eckhardt, R. (1987). *Stan Ulam, John von Neumann, and the Monte Carlo method*. Los Alamos Science (15): 131–137.

Flint, L.E. and Flint, A.L., (2014), *California Basin Characterization Model: A Dataset of Historical and Future Hydrologic Response to Climate Change*, (ver. 1.1, May 2017): U.S. Geological Survey Data Release

Geoscience (2020a). *Santa Ana River Waste Load Allocation Model Update*. Prepared for the Santa Ana Watershed Project Authority, June 2020.

Geoscience (2020b). *Upper Santa Ana River Integrated Model Summary Report*. Prepared for the San Bernardino Valley Municipal Water District, September 2020.

Giuliani, M., Castelletti, A., Amigoni, F., & Cai, X. (2015). *Multiagent Systems and Distributed Constraint Reasoning for Regulatory Mechanism Design in Water Management.* Journal of Water Resources Planning and Management, *141*, 04014068. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000463https://doi.org/10.1061/(ASCE)WR.1943-5452.0000463

Groves, D.G., Molina-Perez, E., Bloom, E., Fischbach, J.R. (2019). Robust Decision Making (RDM): Application to Water Planning and Climate Policy. In: Marchau, V., Walker, W., Bloemen, P., Popper, S. (eds) Decision Making under Deep Uncertainty. Springer, Cham. https://doi.org/10.1007/978-3-030-05252-2_7

Groves, D., and Syme, J. (2022). *Metropolitan Water District of Southern California Case Study.* Metropolitan Water District of Southern California Case Study | RAND. Accessed February 11, 2022.

Guillaume J.H.A., Hunt R.J., Comunian A., Blakers R.S., Fu B. (2016). *Methods for Exploring Uncertainty in Groundwater Management Predictions.* In: Jakeman A.J., Barreteau O., Hunt R.J., Rinaudo JD., Ross A. (eds) Integrated Groundwater Management. Springer, Cham.

Jenkins, K., Surminski, S., Hall, J., & Crick, F. (2017). *Assessing Surface Water Flood Risk and Management Strategies under Future Climate Change: Insights from an Agent-Based Model. Science of the Total Environment*, *595*, 159–168. https://doi.org/10.1016/J.SCITOTENV.2017.03.242

Johnson, J (2010). *Framework to Effectively Quantify and Communicate Groundwater Model Uncertainty to Management and Clients*. Bureau of Reclamation, Pacific Northwest Regional Office.

Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J. (2013). *Many Objective Robust Decision Making For Complex Environmental Systems Undergoing Change*. Environ. Model. Software, 42 (2013), pp. 55-71

Kiefer J. (2016). *Uncertainty in Long-Term Water Demand Forecasts: A Primer on Concepts and Review of Water Industry Practices*. The Water Research Foundation, 2016.

Maliva (2019). *Anthropogenic Aquifer Recharge: WSP Methods in Water Resources Evaluation Series* No. 5. Chapter 24. doi: 10.1007/978-3-030-11084-0_24. 2019.

Marchau, V. A. W. J., Walker W. E., Bloemen, P. J. T. M., and Popper S. W. (2019). *Decision Making under Deep Uncertainty: From Theory to Practice.* Springer Nature https://doi.org/10.1007/978-3-030-05252-2

Merkel and Associates (2006). *Evapotranspiration Analysis of the Prado Basin Santa Ana River, California*. Prepared for Wildermuth Environmental, Inc. 2006.

Miro, Michelle E., et al. (2018). *Estimating Future Water Demand for San Bernardino Valley Municipal Water District.* Prepared for San Bernardino Valley Municipal Water District, December 2018.

Miro, Michelle E., et al. (2021). *Adaptive Water Management in The Face Of Uncertainty: Integrating Machine Learning, Groundwater Modeling And Robust Decision Making.* Climate Risk Management, 34, https://doi.org/10.1016/j.crm.2021.100383

Middlemis H. and Peeters L.J.M. (2018) *Uncertainty analysis—Guidance for Groundwater Modelling Within a Risk Management Framework.* A report prepared for the Independent Expert Scientific Committee on Coal Seam Gas and Large Coal Mining Development through the Department of the Environment and Energy, Commonwealth of Australia 2018.

Moran, T. (2016). *Projecting Forward: A Framework for Groundwater Model Development Under the Sustainable Groundwater Management Act.* December 2016.

MWH (2016). *SGMA Alternative Groundwater Sustainability Plan – Bridge Document for the Indio Subbasin.* Prepared for the Coachella Valley Water District, December 2016.

Niswonger Richard G., Panday, Sorab, and Ibaraki, Motomu (2018). *MODFLOW-NWT, A Newton Formulation for MODFLOW-2005*: U.S. Geological Survey Techniques and Methods 6-A37, 44 p. [Report]. - Reston, Virginia: U.S. Geological Survey, 2011.

Oxnard, City of (2017). Public Works Integrated Master Plan – Water Project Memorandum 2.2 Water Demand Projections. Revised final report. September 2017. https://www.oxnard.org/wp-content/uploads/2017/09/PM-2.2.pdf

PCMDI (2021). CMIP6 - *Coupled Model Intercomparison Project Phase 6, Program for Climate Model Diagnosis & Intercomparison*. Last access on 10/12/2021.

Quinn, J. D., Reed, P. M., Giuliani, M., & Castelletti, A. (2017). Rival *Framings: A Framework for Discovering How Problem Formulation Uncertainties Shape Risk Management Trade-Offs In Water Resources Systems. Water Resources Research*, *53*, 7208–7233. https://doi.org/10.1002/2017WR020524

Santa Cruz, City of. *Santa Cruz Mid-County Groundwater Basin Groundwater Sustainability Plan*. November 2019.

Tarantola, A. (2005). *Inverse Problem Theory and Methods for Model Parameter Estimation*. SIAM.

Taylor, K.E., Stouffer R.J., Meehl G.A. (2012). *An Overview of CMIP5 and the Experiment Design*." Bull. Amer. Meteor. Soc., **93**, 485-498, doi:10.1175/BAMS-D-11-00094.1, 2012.

Thorarinsdottir, Thordis L., et al. (2020). *Evaluation of CMIP5 and CMIP6 Simulations of Historical Surface Air Temperature Extremes Using Proper Evaluation Methods*. Environmental Research Letters. 15 (12).

United States Army Corps of Engineers (2015). 2015 LiDAR of Santa Ana River, holes filled with IFSAR data. Data requested on June 7, 2018; retrieved on July 2, 2018. US Army Corps of Engineers, Los Angeles District, Hydrology and Hydraulics Branch, 2015.

United States Department of the Interior – Bureau of Reclamation. *Colorado River Basin Water Supply and Demand Study: Technical Report A – Scenario Development.* December 2012.

Valley Water (2022). Water Demand Study. https://www.valleywater.org/your-water/water-supply-planning/water-demand-study.

Watermark Numerical Computing (2020). *PEST Groundwater Data Utility Suite.* Accessed at: *https://www.pesthomepage.org*

Watson, A.A., and Kasprzyk, J.R. (2017). *Incorporating Deeply Uncertain Factors into the Many Objective Search Process.* Environ. Model. Software, 89 (2017), pp. 159-171

White, Jeremy T. (2018). *A Model-Independent Iterative Ensemble Smoother for Efficient History Matching and Uncertainty Quantification in Very High Dimensions.* Environmental Modelling and Software 109 (2018) 191–201

White, Jeremy T., Hunt, Randall J., Fienen, Michael N., Doherty, John E. (2020). *Approaches to Highly Parameterized Inversion: PEST++ Version 5, a Software Suite for Parameter Estimation, Uncertainty Analysis, Management Optimization and Sensitivity Analysis.* Water Availability and Use Science Program. Techniques and Methods 7–C26.

Wildermuth Environmental, Inc. (WEI). (2009). *Production Optimization and Evaluation of the Peace II Project Description*. Prepared for the Chino Basin Watermaster, November 2009.

WEI. (2015). 2013 *Chino Basin Groundwater Model Update and Recalculation of the Safe Yield Pursuant to the Peace Agreement*. Prepared for the Chino Basin Watermaster, October 2015.

WEI. (2018a). *2018 Recharge Master Plan*. Prepared for the Chino Basin Watermaster, September 2018.

WEI. (2018b). *Storage Framework Investigation*. Prepared for the Chino Basin Watermaster, October 2018.

WEI. (2020). *2020 Safe Recalculation Final Report*. Prepared for the Chino Basin Watermaster, May 2020.

West Yost (2021). *Evaluation of the Local Storage Limitation Solution*. Prepared for the Chino Basin Watermaster, February 2021.

Wu, W., Maier, H. R., Dandy, G. C., Leonard, R., Bellette, K., Cuddy, S., & Maheepala, S. (2016). *Including Stakeholder Input In Formulating and Solving Real-World Optimisation Problems: Generic Framework and Case Study.* Environmental Modelling and Software, 79, 197–213. https://doi.org/10.1016/j.envsoft.2016.02.012

Attachment A

Applying PESTPP-IES to Generate Calibrated Parameter Realizations

ATTACHMENT A. APPLYING PESTPP-IES TO GENERATE CALIBRATED PARAMETER REALIZATIONS

Attachment A documents the effort to understand and demonstrate the applicability of using PESTPP-IES to calibrate and generate calibrated realizations of the Chino Valley Model (CVM), as demonstrated on a smaller, idealized (synthetic) model. Our goal is to understand (1) how to generate horizontal hydraulic conductivity (HK) distribution fields from pilot points that can be used by PEST and PESTPP-IES as input parameters, (2) how to generate calibrated parameter realizations with PESTPP-IES, and (3) how to run a model using the ensemble of calibrated parameter realizations.

This synthetic model, adapted from Using PESTPP-IES (Doherty, 2021), is used as an example to illustrate the steps generate an ensemble of calibrated parameter realizations and to conduct model simulations with the ensemble of calibrated parameter realizations.

A.1 Overview of the Synthetic Model

The model has three layers and several observation points in each model layer, as shown in Figure A-1. The elevation of the top of the first model layer ranges from 137.5 to 178 meters and each model layer has a constant thickness of 50 meters. The western (left) boundary of the first model layer is a constant head boundary with the head value of 150 [m]. The model cells in an impervious area on the eastern (right) boundary are set as inactive cells and excluded from the flow simulation. All other model boundaries are impervious boundaries. The model is configured for a steady-state simulation with a single stress period. The model domain has a constant recharge rate of 0.002 [m/day]. There are two pumping wells in layer 3 with the pumping rates of 30,000 [m3/day] and 40,000 [m3/day], respectively.

The observed head values at the observation points are specified. The values and distribution of the horizontal hydraulic conductivity (HK) and vertical hydraulic conductivity (VK) in the model layers need to be adjusted to minimize the difference between the model-calculated and observed head values. A variogram is available and is assumed to be applicable to HK and VK in all model layers.

The parameter estimation software PESTPP-IES will be used to calibrate the model and generate calibrated parameter realizations. Many commercial graphical user interface software (GUI) for MODFLOW can be used to develop model input files. The files of the present example are available upon request.

A.2 The Pilot Point Method

Conventional calibration uses the method of parameter zones. This methodology involves defining a limited number of zones in each model layer and assigning parameters within each zone as constant values. Parameters are then adjusted to calibrate the parameters until the fit between model-calculated and observed data is as good as possible. If the goodness of fit obtained based on these zones was not acceptable, then extra zones would be introduced into the model domain and calibration process would be repeated.

There are several shortcomings associated with the parameter zone approach. First, the procedure can be time-intensive. Second, zones of piecewise uniformity are a coarse approximation of the nature of the aquifer material, and using zones limits the ability to explore the effects of small-scale heterogeneities on model predictive uncertainty.

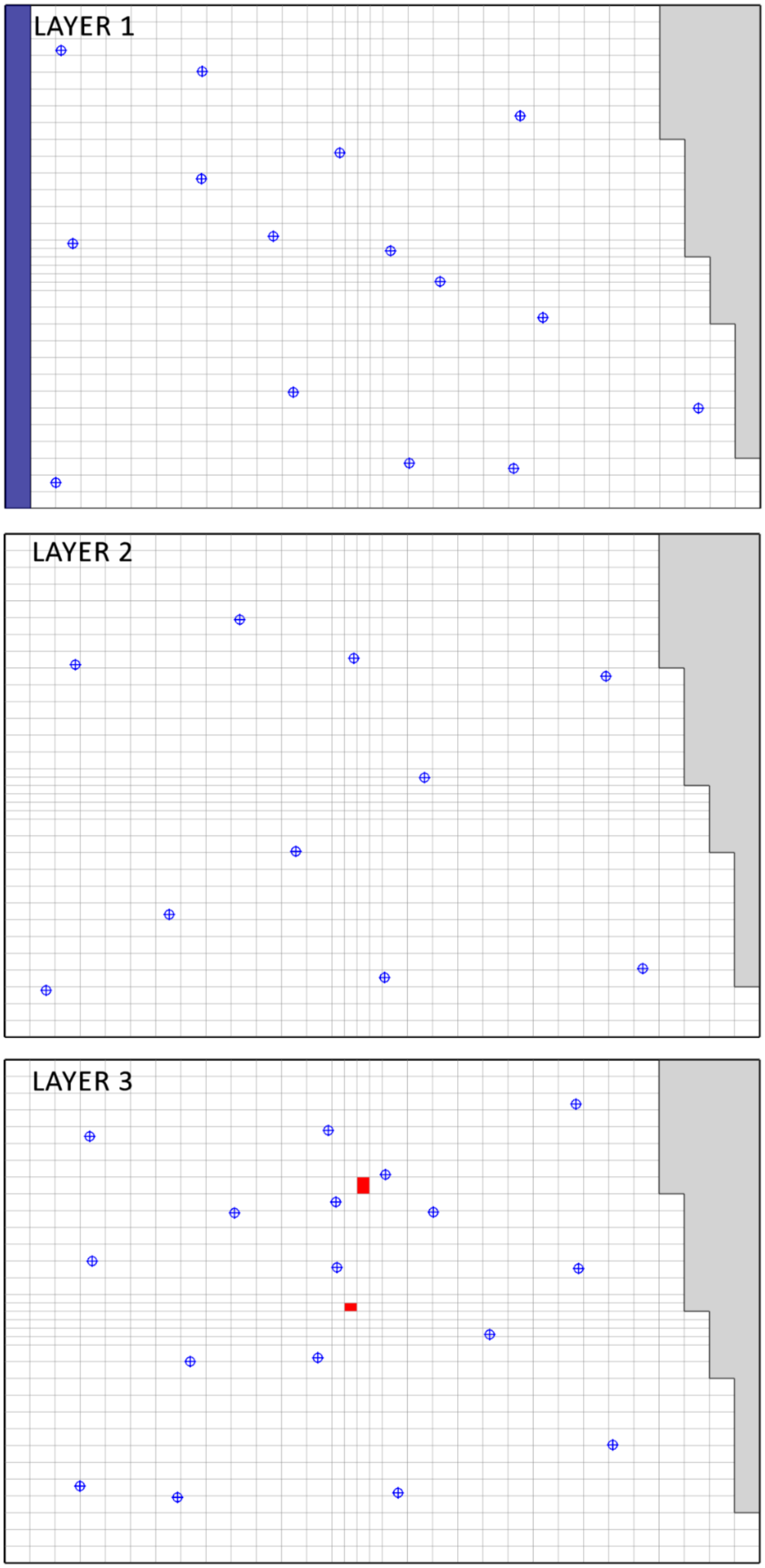


Figure A-1. Layers and Head Observation Points of the Synthetic Model. Red blocks in Layer 3 represent the pumping wells.

The Pilot Point Method can be used to overcome these problems. In this method, several points with hydraulic parameters (i.e., HK and VK values in the present example) are introduced to the model domain, such as shown in Figure A-2. PEST is used to adjust the hydraulic parameters at each pilot point.

Two utility programs, PPK2FAC and FAC2REAL, from the PEST Groundwater Data Utility suite (Watermark Numerical Computing, 2020) can be used to spatially interpolate hydraulic properties associated with the pilot points to the model cells based on the Kriging method. Details of these utility programs are given in the next section.

PPK2FAC undertakes the first stage of the Kriging method. PPK2FAC generates a set of Kriging factors based on the pilot point locations and user-supplied, nested variograms, each with an arbitrary magnitude and direction of anisotropy. Individual pilot points can be assigned to different zones within the model domain. Only those points assigned to a particular zone can be used in calculating parameter values throughout that zone using the Kriging interpolation procedure. The variogram upon which Kriging is based can be different in each zone, reflecting differences in the geology, or in the level of heterogeneity, expected within each geological unit. If only one pilot point is assigned to a particular zone, then a uniform parameter value is assigned to all cells within that zone.

FAC2REAL undertakes the second stage of the Kriging method. FAC2REAL calculates the interpolated value at each model cell as the sum of the products of the Kriging factor and hydraulic property of the pilot points within the search range of the cell. Upper and lower limits can be applied to interpolated values if desired. The calculation results are saved in a MODFLOW-compatible real array file.

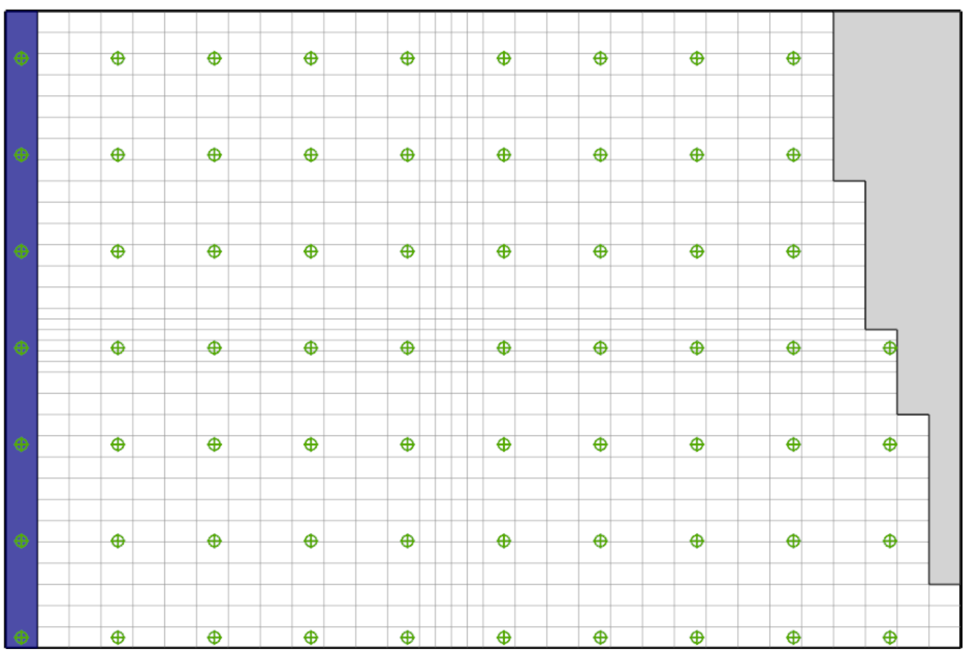


Figure A-2. Pilot points

A.3 Spatial Interpolation with Pilot Points

This section demonstrates the use of the utility programs PPK2FAC and FAC2REAL. First, PPK2FAC will be used to create a Kriging factor file, and then FAC2REAL will be used to spatially interpolate HK values associated with pilot points to model cells. The required input data files for these programs are shown below. The formats of these files are specified in the PEST suite (Doherty, 2018) and PEST Groundwater Data Utility suite (Watermark Numerical Computing, 2020).

- PPK2FAC input files:
  - Grid specification file: defines the grid location and column/row spacing.
  - Pilot points file: defines the location of pilot points.
  - Zonal integer array file: an integer array containing the pilot point zones.
  - Structure file: defines structures with variograms.
- FAC2REAL input files:
  - Kriging factor file: contains kriging factors calculated by PPK2FAC
  - Pilot points file: defines the location of pilot points.

Calculation of Kriging factors can be a very time-consuming task if the number of pilot points is large. Fortunately, Kriging factors are independent of the values assigned to the pilot points and therefore just need to be calculated once for each set of pilot points.

A.3.1 Running PPK2FAC

The utility program can be started by double-clicking the executable file “ppk2fac.exe” in Windows Explorer. Once the program is started, it will prompt for user’s input. Figure A-3 shows the prompts and the corresponding user’s inputs in red. In the present example, the calculated kriging factors are stored in the file “krigingfactor1.dat.”

The utility program can also be started in a Windows Command Prompt by typing “ppk2fac < ppk2fac.in” followed by Enter. This instructs PPK2FAC to read the user’s input from the text file “ppk2fac.in” that contains the pre-recorded user’s inputs.

Generation of MODFLOW and MT3D input arrays based on PPK2FAC-generated Kriging factors is carried out by FAC2REAL. Separation of the time-consuming, factor-generation process from the array construction process facilitates automatic parameter estimation based on pilot points using software such as PEST, for Kriging factors are unchanged as values assigned to the pilot points are adjusted through the parameter estimation process (Watermark Numerical Computing, 2020).

A.3.2 Running FAC2REAL

The utility program FAC2REAL can be started by double-clicking the executable file “fac2real.exe” in Windows Explorer. Once the program is started, it will prompt for user’s input. Figure A-4 shows the prompts and the corresponding user’s inputs in red. The pilot point file “points1.dat” and the output file “krigingfactor1.dat” from PPK2FAC is used as input to FAC2REAL. The interpolation results are stored in the file “kx1.dat”. Figure A-5 shows a contour map based on the interpolation results of the synthetic model.

The utility program can also be started in a Windows Command Prompt by typing “fac2real < fac2real.in” followed by Enter. This instructs FAC2REAL to read the user’s input from the text file “fac2real.in” that contains the pre-recorded user’s inputs.

The hydraulic property values assigned to the pilot points can be different from those provided in the pilot points file read by PPK2FAC. Nevertheless, it must list the same points in the same order, and each point must be assigned to the same zone.

```
Program PPK2FAC calculates point-to-cell factors by which kriging is
undertaken from a set of pilot points to the finite-difference grid.

Enter name of grid specification file: pest.gridspecification
        – grid specifications read from file pest.gridspecification
Enter name of pilot points file: points1.dat
        – data for 67 pilot points read from pilot points file points1.dat

Enter minimum allowable points separation: 0
Enter name of zonal integer array file: zones.dat
Is this a formatted or unformatted file? [f/u]: f
        – integer array read from file zones.dat
Enter name of structure file: struct.dat

The following zones have been detected in the integer array:
        For zone characterized by integer value of 1:-
        Enter structure name (blank if no interpolation for this zone): struct1
        Perform simple or ordinary kriging [s/o]: o
        Enter search radius: 2970
        Enter minimum number of pilot points to use for interpolation: 1
        Enter maximum number of pilot points to use for interpolation: 12

Enter name for interpolation factor file: krigingfactor1.dat
Is this a formatted or unformatted file? [f/u]: f
Enter name for output standard deviation array file: standarddeviation.dat
Write a formatted or unformatted file? [f/u]: f
Enter name for regularization information file: regularizationinfo.dat

Carrying out interpolation for integer array zone 1....
        Number of pilot points for this zone    =   67
        Mean data value for these pilot points  =   44.849
        Data standard deviation for these points =   31.894
        Working…
```

Figure A-3. Screen prompts of the utility program PPK2FAC and the user’s inputs in red.

Program FAC2REAL carries out spatial interpolation based on interpolation factors calculated by PPK2FAC and pilot point values contained in a pilot points file.

Enter name of interpolation factor file: **krigingfactor1.dat**
Is this a formatted or unformatted file? [f/u]: **f**

Enter name of pilot points file [points1.dat]: **points1.dat**
– data for 67 pilot points read from pilot points file points1.dat

Supply lower interpolation limit as an array or single value? [a/s]: **s**
Enter lower interpolation limit: **1e-10**

Supply upper interpolation limit as an array or single value? [a/s]: **s**
Enter upper interpolation limit: **1e10**

Enter name for output real array file: **kx1.dat**
Write a formatted or unformatted file? [f/u]: **f**

Figure A-4. Screen Prompts of the utility program FAC2REAL and user's inputs in red

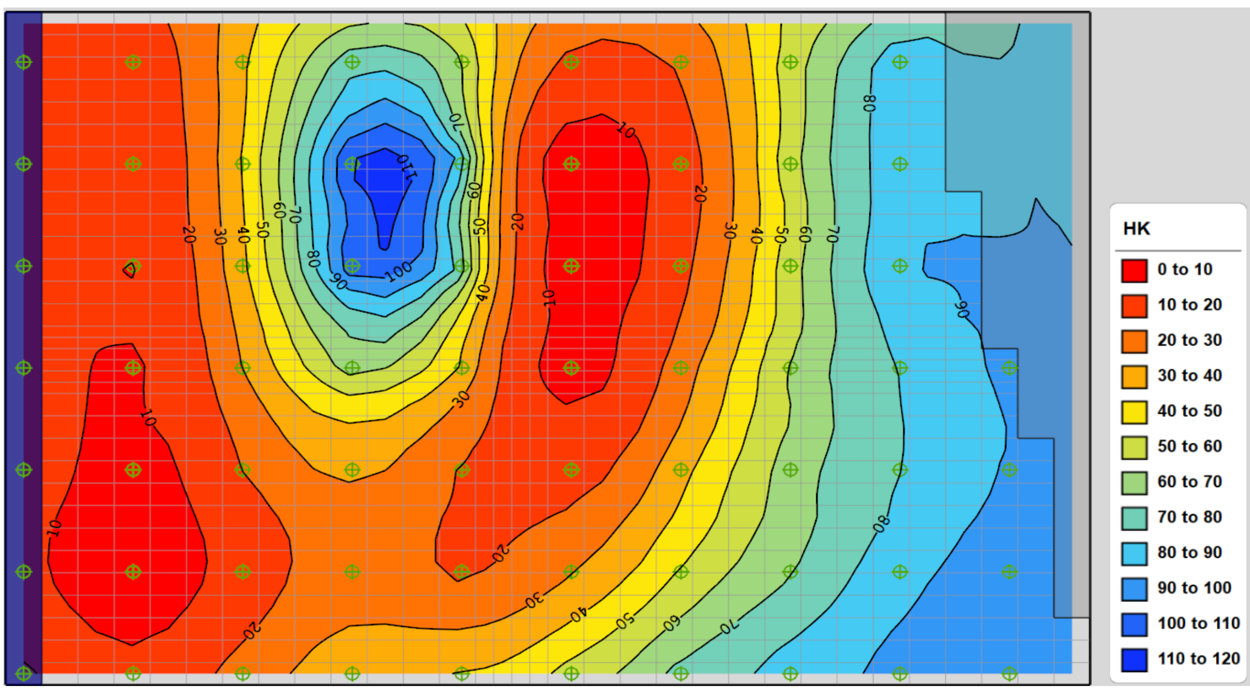


Figure A-5. A contour map based on the interpolation results created by FAC2REAL

A.4 Using the Pilot Point Method with PEST

Pilot points are integrated to a model by creating a batch file and inserting the name of a batch file to the "* model command line" section of a PEST control file. The batch file contains several instructions that together form a "composite model" used by PEST. Such a "composite model" includes instructions to manipulate data (such delete files, invoke utility programs, start model run, and postprocess model results) for a PEST iteration.

A.4.1 A Simple Composite Model

A simple composite model can consist of just a few instruction lines shown below.

```
del hk1.dat
fac2real < fac2real.in
mf2005 mymodel.nam
targpest
```

The lines of the simple composite model are as follows.

- The first line "del hk1.dat" deletes the "hk1.dat" file that contains the interpolated HK values from the previous calibration iteration.
- The second line "fac2real < fac2real.in" instructs FAC2REAL to read input values from the fac2real.in file. FAC2REAL generates the hk1.dat file based on the values associates with the pilot points that are updated by PEST for the current iteration of the calibration process. Note that the same kriging factor file cited in fac2real.in is reused for each iteration.
- The line "mf2005 mymodel.nam" starts MODFLOW-2005 with the Name file "mymodel.nam". The hk1.dat file is included in the "mymodel.nam" file as a part of the model input.
- The last line "targpest" runs the utility program Targpest, which extracts the model output data and save them in a form that can be read by PEST through specific instruction files need to be designed to match the output format of targpest. TARGPEST is distributed with the commercial software Groundwater Vistas. See its manual for details.

A.4.2 A Complex Composite Model

The batch file shown in Figure A-6 is an example of a complex composite model. Note that "mod2obs.exe," "layerweight.exe," "streamgage.exe," and "lakestage.exe" are utility programs of Processing Modflow (Chiang, 2022) that are designed to extract the model results and store the extracted data in the formats that can be read by PEST. Specific instruction files are designed in Processing Modflow to match the output of those utility programs.

```
del kx_array
del kz_array
fac2real < fac2real1.in
fac2real < fac2real2.in
MODFLOW-NWT_64.exe mymodel.nam
mod2obs.exe < pest.mod2obsheadinput
layerweight.exe pest.boreinfo pest.mod2obsheadoutput pest.headoutput
mod2obs.exe < pest.mod2obsdrawdowninput
```

Figure A-6. A complex composite model

The lines of the above example are as follows.

- The lines “del kx_array” and “del kz_array” respectively delete the kx_array and kz_array files that contain the interpolated HK and VK values from the previous calibration iteration.
- The line “fac2real < fac2real1.in” instructs FAC2REAL to read input values from the “fac2real1.in” file. FAC2REAL generates the kx_array file based on the values associates with the pilot points that are updated by PEST for the current iteration of the calibration process.
- The line “fac2real < fac2real2.in” instructs FAC2REAL to read input values from the “fac2real2.in” file. FAC2REAL generates the kz_array file based on the values associates with the pilot points that are updated by PEST for the current iteration of the calibration process.
- The line “MODFLOW-NWT_64.exe mymodel.nam” starts MODFLOW-NWT with the Name file “mymodel.nam.” The kx_array and kz_array files are cited in the “mymodel.nam” file as a part of the model input.
- The line “mod2obs.exe < pest.mod2obsheadinput” instructs MOD2OBS to read input values from the pest.mod2obsheadinput file. MOD2OBS interpolates model calculated cell-based head values to specific observation point locations and times.
- The line “layerweight.exe pest.boreinfo pest.mod2obsheadoutput pest.headoutput” instructs LAYERWEIGHT to read input values from the files cited in the line. LAYERWEIGHT calculates layer-weighted average head values for multi-layer head observations.
- The line “mod2obs.exe < pest.mod2obsdrawdowninput” instructs MOD2OBS to read input values from the pest.mod2obsdrawdowninput file. MOD2OBS interpolates model calculated cell-based drawdown values to specific observation point locations and times.
- The line “layerweight.exe pest.boreinfo pest.mod2obsdrawdownoutput pest.drawdownoutput” instructs LAYERWEIGHT to read input values from the files cited in the line. LAYERWEIGHT calculates layer-weighted average drawdown values for multi-layer drawdown observations.
- The line “streamgage.exe modflow.streamout pest.reach pest.strflowobstimes pest.streamout” instructs STREAMGAGE to read input values from the files cited in the line. STREAMGAGE calculates the weighted streamflow values at the times of interest for each observation point.

- The line “lakegage.exe modflow.lakeout pest.lakeobspt pest.stageobstimes pest.lakeoutput” instructs LAKEGAGE to read input values from the files cited in the line. LAKEGAGE calculates the weighted stage values at the times of interest for each observation point.

A.4.3 A Complete PEST Control File

Figure A-7 shows a complete PEST control file that includes the batch file “modelrun.bat” in the “* model command line” section. The modelrun.bat represents a complex composite model as shown in Figure A-6.

The lines in the “parameter data” section of the PEST control file list the names, initial values, and minimum/maximum bounds of parameters.

The first six lines in the “model input/output” section of the PEST control file list two pairs of “pilot point template file and pilot point file.” A template file contains the parameter names that PEST will replace with estimate values of the corresponding parameters. Once the parameter names in a template file are replaced with values. PEST writes the results to the corresponding pilot point file. The pilot point files with updated parameter values are interpolated to model cells by FAC2REAL in the next iteration.

The last line in the “model input/output” section of the PEST control file list pairs of the instruction file and corresponding output file from the composite model. This instruction file is tailored to instruct PEST to correctly read desired model output data from the matching output file. Those model output data are compared with the observed counterparts during the parameter estimation process. For details of the PEST control file, template file, and instruction file, see the PEST manual (Doherty, 2018).

```
pcf
* control data
restart estimation
            402      42       2        0        3
6 1 single point 1 0 0
20 -3.0 0.3 0.01 7 999 lamforgive
10 10 0.001
0.1 1 noaui noboundscale
50 0.01 3 3 0.01 3
0 0 0 PARSAVEITN
* singular value decomposition
      1
      402 5.0e-007
      1
* parameter groups
Kp          relative    0.01 0      switch 2 parabolic
Kz          relative    0.01 0      switch 2 parabolic
* parameter data
KpKp1 log factor 100 1 10000 Kp 1.0 0.0 1
      [lines deleted]
KzKz200 log factor 10 0.1 1000 Kz 1.0 0.0 1
KzKz201 log factor 10 0.1 1000 Kz 1.0 0.0 1
* observation groups
head1
head2
head3
* observation data
o1 163.04 1 Head1
o2 154.00 1 Head1
[lines deleted]
o42 156.90 1.5 Head3
* model command line
modelrun.bat
* model input/output
points1.tpl points1.dat
points2.tpl points2.dat
```

Figure A-7. A Complete PEST Control File

A.5 Steps to Calibrate Model and Generate Calibrated Parameter Realizations

PESTPP-IES can be used to calibrate a model and generate calibrated parameter realizations for the model at the same time. Two types of files are required to enable this feature of PESTPP-IES — a Parameter Uncertainty File and a Covariance Matrix File. The Parameter Uncertainty File acts a container of all covariance files of a model. The Covariance Matrix File contains the covariance of pairs of parameters.

A.5.1 Covariance Matrix File

Covariance matrix files can be generated by using the PPCOV utility from the PEST Groundwater Data Utility suite. The utility program PPCOV can be started by double-clicking the executable file "ppcov.exe" in the Windows Explorer. Once the program is started, it will prompt for user's input. Figure A-8 shows the prompts and the corresponding user's inputs in red. The pilot point file "points1.dat" and the "struct.dat" files are used as input to PPCOV and the calculated covariance matrix is stored in the "cov_kx1.mat" file.

Program PP2COV prepares a covariance matrix file for pilot point parameters
based on a geostatistical structure file.

Enter name of pilot points file: **points1.dat**

– data for 67 pilot points read from pilot points file points1.dat

Enter minimum allowable separation for points in same zone: **0**

Enter name of structure file: **struct.dat**

Enter structure to use for pilot point zone 1: **struct1**

Enter name for output matrix file: **cov_kx1.mat**

Enter pilot point prefix for parameter name (<Enter> if none): **kp**

Filling covariance matrix....

– file cov_hk1.mat written ok.

Warning: in any future processing of this covariance matrix, sensitivities
for parameters with a log-variogram must be taken with respect to the log
of the parameters.

Figure A-8. Screen prompts of the utility program PP2COV and the user's inputs in red.

A.5.2 Parameter Uncertainty File

PESTPP-IES requires a parameter uncertainty file that defines the covariance matrices of the estimable parameters. Figure A-9, for example, shows a parameter uncertainty file that contains two covariance matrix files for the first model layer of the example model – "cov_kx1.mat" for the HK parameters and "cov_kz1.mat" for the VK parameters. The product of a matrix and the corresponding variance_multiplier is the covariance between parameter pairs that is used by PESTPP-IES.

```
START COVARIANCE_MATRIX
    file cov_kx1.mat
    variance_multiplier 0.25
END COVARIANCE_MATRIX

START COVARIANCE_MATRIX
    file cov_kz1.mat
    variance_multiplier 0.25
END COVARIANCE_MATRIX
```

Figure A-9. A Parameter Uncertainty File that defines covariance matrices of estimable parameters

A.5.3 Running PESTPP-IES

Once a parameter uncertainty file and its related covariance matrix files are created, they can be included in a PEST control file that can be used by PESTPP-IES to calibrate and generate calibrated parameter realizations in the following way.

First, insert the lines shown in Figure A-10 to the end of a PEST control file. The line "++ies_num_reals(80)" set the desired number of calibrated parameter realizations; the line "++parcov(param.unc)" informs PESTPP-IES the name of the Parameter Uncertainty file; the line "++ies_subset_size(2)" instructs PESTPP-IES to devote two realizations to determining the best Marquardt lambda and line search factor to use during each iteration; the last line "++ies_save_binary(true)" instructs PESTPP-IES to record iteration-specific, updated parameter ensembles, as well as corresponding iteration-specific, updated model output ensembles, in binary JCB files (use "++ies_save_binary(false)" to save ASCII files). If the parcov() control variable is omitted from a PEST control file, then PESTPP-IES calculates prior uncertainties from parameter bounds supplied in that control file.

```
++ ies_num_reals(80)
++ parcov(param.unc)
++ ies_subset_size(2)
++ ies_save_binary(true)
```

Figure A-10. Lines to invoke the iterative ensemble smoother of PESTPP-IES

Once the lines shown in Figure A 10 are inserted to the PEST control file, PESTPP-IES can be started by running the following command in Command Prompt. This line starts the executable "ipestpp-ies.exe" and instructs it to read the PEST control file "example.pst".

```
ipestpp-ies example.pst
```

A.6 PESTPP-IES Output Files

All output files written by PESTPP-IES use the same filename base as the PEST control file. In our present example, some of the output files are JCB files as the line "++ies_save_binary(true)" was included in the PEST control file. The JCB files contain parameter and observation values comprising each parameter and observation realization; the iteration number to which these values pertain is included in the filename extension, "example.N.par.jcb" and "example.N.obs.jcb" respectively, where N is the iteration number.

PESTPP-IES also writes the "example.phi.actual.csv" file that stores the iteration-by-iteration history of the objective functions. Inspecting of this file allows the modeler to determine the goodness of the fit.

A.7 Inspecting Parameter Ensembles

The program JCB2CSV (a member of the PEST suite of utility support programs) can be used to convert the contents of a JCB file to a CSV file. To obtain a CSV file listing parameter values comprising all realizations updated during iteration 10, use the command:

jcb2csv example.10.par.jcb example.10.par.csv nt

The "nt" component of the above command stands for "no transpose". Each row of the resulting CSV file contains a single parameter realization. If you prefer that parameter realizations be ascribed to columns rather than rows, use the above command with "t" (for transpose) instead of "nt".

If you import file "example.10.par.csv" into EXCEL, you will note that realizations are named "base" and then "0" to "78", this amounting to 80 realizations in all. Initial parameter values for the base realization are initial parameter values in the PEST control file.

A.8 Running a Model using Ensembles

Individual parameter realizations stored in a JCB file can be extracted and applied to a calibration or projection model in the following steps. A simple script (for example, written in Python) can be used to automate the process.

1. The JCB2PAR utility (supplied with the PEST suite) is used to extract an individual parameter realization from a JCB file and save the parameters in a PEST parameter value file (i.e., a PAR file). The following command, for example, extract the 60th parameter realization from iteration 10 to the PEST parameter value file "realization60.par".

   jcb2par example.10.par.jcb 60 realization60.par

2. Replace the parameter values in the pilot points files (for the present example, "points1.dat", "points2.dat", etc.) with the parameter values in the PEST parameter value file.
3. Use FAC2REAL as shown in Section A.3.2 to create MODFLOW-compatible parameter matrix files with the updated Pilot Points files.
4. Finally, the parameter matrix files can be applied to a MODFLOW model with the REPARRAY utility program or through the MODFLOW Open/Close option in the model's NAME file.

5. The model result (for example, a safe yield time series) of the parameter realization is calculated.
6. Repeat the steps 1 to 5 for all parameter realizations.

Running a model using the ensemble of parameter realizations will yield an ensemble of model results that can be used to quantify the predictive mean and uncertainties.