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TECHNICAL MEMORANDUM

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SENT VIA: EMAIL

TO: Peter Kavounas, Chino Basin Watermaster

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SUBJECT: Conceptual Approaches to Characterize and Address Uncertainty in the Recalculation of the Chino Basin Safe Yield

1.0 Background and Objectives

In 2012, Watermaster began conducting an investigation to recalculate the Safe Yield pursuant to the Peace Agreement. This work was completed in 2015. The investigation developed a methodology for calculating Safe Yield and concluded, based on that methodology, that the Safe Yield for the period 2011 through 2020 was 135,000 afy (WEI, 2015). The methodology used to calculate the Safe Yield 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.*
> 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."

On April 28, 2017, the Court approved the methodology and ordered that the Safe Yield be set to 135,000 afy for the period 2015 through 2020 (Court Order)[1]. Beyond accepting the current methodology, the Court Order also included provisions regarding updating the SY 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."*

Paragraph 4.7 of the 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 SY methodology and the other requirements set forth in the Court Order.

The Safe Yield of the Chino Basin was recalculated in May 2020 using the 2020 Chino Valley Model (CVM) and documented in the *2020 Safe Yield Recalculation Report* (2020 SYR Report) (WEI, 2020). The Court adopted a Safe Yield of 131,000 acre-feet per year for the period of fiscal year 2020/21 through 2029/30. To aid the development of the 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 SY methodology and can be grouped into the following two categories:

- Recommendations to characterize and address uncertainty in the 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)
  - 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)

In FY2020/2021, Watermaster and the Parties collaborated to develop a scope of work to meet the requirements of the Court Order. The initial steps to update the SY methodology are the following:

1. Define various sources of modeling uncertainty that should be considered in the updated SY methodology. Watermaster's Engineer will develop a technical memorandum (TM) outlining

[1] On April 28, 2017, the Superior Court for the County of San Bernardino (Court) issued orders for Watermaster's motion regarding the 2015 Safe Yield Reset Agreement, Amendment of Restated Judgment, Paragraph 6: link

these sources and related questions necessary to answer when updating the SY methodology. Watermaster's Engineer will submit the TM 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 above.
3. Based on feedback from the peer review meeting, Watermaster will work with the Engineer to develop a supplemental scope and budget to complete the update of the SY methodology.

This TM, described in step 1 above, serves as the background and foundation for the process to update the SY methodology in the Chino Basin. This work will be conducted pursuant to paragraph 4.4 of the Court Order and the scope that the Chino Basin Watermaster (Watermaster) developed in collaboration with the Parties to execute this work in fiscal year (FY) 2021/2022. This TM is also responsive to the Parties' comments on the recent SYR Report that relate to characterizing and addressing uncertainty in the CVM. The recommendations to reconsider the 10-year prospective calculation of the Safe Yield could be considered in the update of the SY methodology but is outside of the scope of this TM.

The outline of this TM is:

- **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 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 SY methodology.
- **Section 4: Potential Methods for Characterizing and Addressing Uncertainty.** This section describes potential methods for updating the SY methodology to characterize and address uncertainty.
- **Section 5: Next steps**. This section describes the recommended next steps following the Peer Review meeting.
- **Section 6: References**

2.0 Overview of Uncertainty in Surface Water and Groundwater Modeling

Uncertainty analysis in calibration and prediction 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 prediction scenarios with associated likelihoods, each plausible in that it is consistent with all available information and data. Uncertainty analysis also identifies the main sources of uncertainty and by how much the uncertainty in outcomes can be reduced by incorporating further data into the model (Middlemis and Peeters, 2018). An uncertainty analysis has the benefit of identifying gaps in data or understanding that may inform future monitoring (DWR, 2016).

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.

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. 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 may need to be considered. Uncertainty can be expressed in terms of the parameters used to describe the system or the accuracy in model predictions.

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

2.1.1 Surface Water and Groundwater Model Parameters

Uncertainty exists in the ways that the physical environment is represented in a groundwater 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) hydrologic and hydrogeologic features (e.g., hydrostratigraphy, aquifer geometry, fault barriers to groundwater flow) that are underground and are often not well characterized; and (3) hydrologic processes (e.g., evapotranspiration, streambed recharge, and deep infiltration of precipitation and applied water) that are typically not measured directly. Estimated values of these parameters are usually assigned to a groundwater model during the model construction. These parameters are then adjusted during the calibration process that attempts to minimize the differences between observed historical data and the model-simulated counterparts.

Another related problem regarding uncertainty in groundwater model parameters is the existence of non-unique solutions. 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.

2.1.2 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 groundwater-level data over historical time periods which hampers model calibration).

2.1.3 Supply and Demand 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 ground water management projections. Long-term forecasts of water demands and available water supplies are critical inputs to water utility planning efforts and decision making (Kiefer, J., 2016). Forecasting water supply and demand is uncertain and influenced by macro-socioeconomic and climatic factors, as well as local behavior of consumers (Bruce, A., Brown, C. and Dufour, A., 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 groundwater use in response to climate. Currently, most studies on climate impacts rely on the downscaled results of Global Circulation Models (GCMs) involved in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (Taylor and others, 2012). CIMP5 assumes four Representative Concentration Pathways (RCPs) that describe different climate futures, all of which are considered possible depending on the magnitude of future greenhouse gas (GHG) emissions.

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 GCM projections. 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 (ET_0) is projected to increase (WEI, 2020). As with all model projections, the GCM projections are inherently uncertain. In the near future, the downscaled results of GCMs of the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (PCMDI, 2021) will replace those of CMIP5.

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, starting in 2027, to meet their supplier specific urban water use objective 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 yet been approved by the State Water Board. However, DWR has proposed the following provisional method to calculate a supplier’s ORWU objective:

$$ORWU = (ET_0 - P_{eff}) * (0.7) * (LAs)$$[2]

where, ET_0 is reference evapotranspiration, P_{eff} is effective precipitation, 0.7 is the supplier level evapotranspiration (ET) factor, and LAs is landscape area for a water supplier. 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]). Additionally, the DWR is considering recommending that the supplier level ET factor be reduced to 0.55 for any new development which would lead to additional reductions in outdoor water use.

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.

> *"**8. 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 milestones. Predictive scenarios for the GSP should demonstrate that the sustainability goal will be maintained over the 50-year planning and implementation horizon.*
>
> ***9. 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."*

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

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 SY methodology, as they represent "best management practices" which are referenced in paragraph 4.4 of the Court Order.

3.0 Uncertainty in the CVM and its Use in the Safe Yield Reset

The previous section summarizes 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 CVM. Refer to the 2020 SYR Report for a more detailed description of each model input.

3.1 Surface Water and Groundwater Model Parameters

3.1.1 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. A kriging process was used to spatially interpolate the estimates across the model domain (i.e., the lithological model). The model domain was then subdivided into several parameter zones based on an estimate of logical depositional environments. Each parameter zone was assigned a parameter zone coefficient 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 parameter zone coefficient and the initial hydraulic parameter value derived from the lithological model.

3.1.2 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.

3.1.3 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 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.

3.1.4 Groundwater Evapotranspiration

Groundwater evapotranspiration (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.

3.1.5 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.

3.1.6 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.

3.2 Historical Data

3.2.1 Precipitation

Precipitation is a primary source of water for the 2020 CVM watershed. Estimates of precipitation over the 2020 CVM model domain were developed from precipitation stations operated by the LACFCD, SBCFCD, Riverside County Flood Control and Water Conservation District, 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.

3.2.2 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 and the R4 model.

3.2.3 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

3.2.4 Managed Artificial Recharge

With one exception, estimates of Managed Artificial 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.

3.2.5 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, and the IEUA.

3.2.6 Groundwater Levels

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

3.2.7 Land Use

Historical land use datasets are acquired from the Southern California Association of Governments (SCAG), the DWR, and San Bernardino County. These land use datasets are only 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 the DIPAW term for each of these land use years, and the values were linearly interpolated between land use years.

3.2.8 Potential ET

ET_0 estimates near the 2020 CVM watershed were obtained from the California Irrigation Management Information System (CIMIS) stations located in Pomona and Riverside. The 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.

3.2.9 Evaporation

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

3.2.10 Subsurface Inflow from Adjacent Groundwater Basins

The boundary condition governing the groundwater discharges 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. The range of subsurface inflow from the Arlington Basin to the Temescal Basin was estimated based on the Arlington Basin Model (WEI, 2009).

3.2.11 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 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 also not explicitly accounted for in the CVM.

3.2.12 Septic Tank Discharge

Data for parcels with septic tanks was 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 rates of leakage from septic tanks were applied to increase the groundwater recharge flux of each model cell with septic tanks. These rates were based on changes observed in wastewater inflows to nearby wastewater treatment plants.

3.2.13 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 the deep infiltration of precipitation and applied water (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.

3.3 Supply and Demand Projections

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 their best estimates of their demands and associated water supply plans. Individually and in aggregate, these water demands and associated supply plans were reasonable and the most reliable planning information available at that time.

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, 2020). 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 Methods for Characterizing and Addressing Uncertainty

This section describes potential methods for updating the SY methodology to characterize and address uncertainty.

4.1 Parameterization and Historical Data

CVM consists of two surface-water models (HSPF and R4) and a groundwater model based on MODFLOW-NWT (WEI, 2020). The surface-water models were calibrated manually. R4 was used to estimate DIPAW at the root zone. The estimated DIPAW was used as groundwater recharge to the groundwater model by considering storage and travel time through the vadose zone. The groundwater model was calibrated by conducting a sensitivity analysis of model parameters, using PEST inverse modeling to adjust parameters to improve the model representation of the groundwater system. A residual analysis of the observed versus simulated data was conducted to evaluate and characterize model error.

While the historical data that are used in model calibration are uncertain, it is our professional judgement that a significant 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 CVM is 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, we propose to honor the observed data and focus the analysis on the possible variations of parameters used in the R4 model and the groundwater model. The following steps describe a potential method to address the uncertainties related to aquifer parameters:

1. Select a group of no fewer than 10 parameters of CVM with the highest relative sensitivity. Based on our knowledge and experience with the CVM, we would recommend including hydraulic conductivity, specific yield, magnitude of DIPAW, and vadose zone lag time for inclusion in the uncertainty analysis.
2. Define lower and upper bounds for each selected parameter centered on its calibrated value.
3. Conduct a Monte Carlo (Eckhardt, 1987) simulation 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 realization.
    d. Repeat steps 3.a to 3.c until a defined limit is reached, either in number of realizations (ideally around 10 to maintain tractability) or in number of model runs completed.

4. Run the chosen projection scenarios using the surviving realizations from step 3 (detailed in the following sections).

4.2 Supply and Demand Projections

As documented in the 2020 SYR Report, Safe Yield was calculated based on a single future scenario that was designed based partially on the Parties' best estimates of their water demands and associated supply plans. The SGMA requires that GSPs use the best estimates of water demands and supplies as a baseline condition for evaluating uncertainty in demands and supplies (paragraph 354). Recently developed groundwater models that are used for GSPs employ various assumptions for future supplies and demands to quantify the uncertainty.

This approach could be incorporated into the SY methodology, but an appropriate range of water supply and demand projections must be developed. To design multiple scenarios representing an appropriate range of assumptions, the following steps could be taken:

- Conduct discussions with Watermaster, the Parties, and the municipal water suppliers in the Chino Basin to quantify appropriate ranges in projected water supplies and demands.
- Review historical data and comparison to prior projections to refine assumptions for the possible ranges in water supplies and demands.
- Synthesize and review the data collected and evaluated pursuant to paragraph 4.5 of the Court Order (which may include the items in the bullets above).

4.3 Climate Projections

The climate change factors provided by DWR (DWR, 2018) for projected central tendency climate conditions for 2030 and 2070 conditions are implemented in the current CVM. The DWR recommends using these factors to project future hydrologic conditions in GSPs, and these factors were used in development of many GSPs (e.g., Central Kings GSP, Tule Basin Groundwater Model Report, Salinas Valley GSPs). These change factors are based on the ensemble average of 20 GCMs of CMIP5 that were, at that time, the most up-to-date readily available climate projection datasets. In addition to these two datasets, DWR also provided two 2070 extreme scenarios (i.e., one drier with extreme warming and one wetter with moderate warming). Climate modeling is a rapidly evolving field, and newer climate projection datasets are or will soon be available, including the Sixth Coupled Model Intercomparison Project (CMIP6) and USGS datasets (e.g., Flint, L.E. and Flint, A.L., 2014).

Using gridded datasets of high-resolution climate projections would result in a more robust simulation of future climate than change factors but would be more time-intensive to suit the available data to the needs of the CVM. These tradeoffs should be considered to increase the robustness of the projection scenarios, and therefore, the Safe Yield calculation.

4.4 Potential Process for Calculating Safe Yield

To facilitate discussion at the first peer review meeting, the following potential process for calculating the Safe Yield is included below. The actual proposed SY Methodology will incorporate the feedback and suggestions after the peer review is concluded.

1. Generate multiple realizations of calibrated model. Choose a subset of realizations to use if necessary or desired.
2. Generate ensemble of projection scenarios based on each chosen realization. The total number of models in the ensemble would be the number of chosen realizations times the number of projection scenarios.
3. Weight the projection scenarios to guide the interpretation of the model results. Weighting methods can be as simple as assuming that each scenario has an equal likelihood to determining weights based on potential risks or another method. These methods will be further developed in later phases of the SY methodology development.
4. Applying likelihoods to the ensemble and the chosen evaluation period to determine the Safe Yield.

5.0 NEXT STEPS

This TM will serve as a basis for discussion at the first peer review meeting on October 26, 2021. At the peer review meeting, Watermaster and Watermaster's Engineer will present and discuss the contents of this TM and gather feedback from the peer review committee. Subsequently, Watermaster will work with the Engineer to develop a supplemental scope and budget to refine the draft proposed SY methodology.

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