The purpose of this technical memorandum is to provide the background, methods, and results of the end-of-year 2022 Salton Sea playa exposure estimate, as well as information about actual playa exposure versus projected playa exposure.

1 BACKGROUND

This section discusses the background of the Salton Sea Air Quality Mitigation Program (SSAQMP; IID 2016) and the fluctuations of the Salton Sea’s elevation since its formation in 1905.

1.1 SALTON SEA AIR QUALITY MITIGATION PROGRAM

The SSAQMP (IID 2016) was developed for the Imperial Irrigation District (IID) in cooperation with the Imperial County Air Pollution Control District (ICAPCD). The SSAQMP is a comprehensive, science-based, adaptive approach to address air quality mitigation requirements associated with the transfer of up to approximately 300,000 acre-feet per year of conserved water under the Quantification Settlement Agreement (QSA). The conserved water transfer reduces the volume of agricultural return flow to the Salton Sea, resulting in increased salinity and lower water elevations (Barnum et al. 2017). Receding water exposes playa (dry lakebed), increasing the potential for dust emissions that could affect communities near and around the Sea.

The objective of the SSAQMP is to proactively detect, locate, assess, and identify options to mitigate dust emissions from exposed Salton Sea playa. It has three main components: 1) an annual Emissions Monitoring Program (IID 2023a, In Progress) to map playa exposure, estimate emissions, and identify high-priority areas of exposed playa for proactive dust control, 2) an annual Proactive Dust Control Plan (PDCP) (IID 2023b, In Progress) with recommendations and design for site-specific dust control measures (DCMs), and 3) implementation of DCMs (e.g., surface roughening and vegetation establishment).

Estimation of actual playa exposure is completed as a part of the Annual Emissions Monitoring Program (IID 2023a, In Progress) described above. The following sections describe the playa exposure mapping results for end-of-year 2022 that will be used in the Annual Emissions Estimate for the 2022/2023 monitoring year.
1.2 Salton Sea Elevation

The Salton Sea was formed in 1905 when the Colorado River was diverted west into the Salton Trough. After its formation, the Salton Sea’s elevation decreased dramatically from the flood-driven high stand in 1907 to an all-time low in 1925 (Figure 1). The Salton Sea’s elevation then steadily climbed into the 1980s and 1990s (Figure 1). Around 2000, the Salton Sea elevation began declining. The declining elevations are due to declining inflows from Mexico, evolving agricultural practices (including increases in irrigation efficiency), climate change, and more recently a reduction in agricultural return flows associated with the QSA (Barnum et al. 2017).

In addition, the Salton Sea is a terminal water body, and evaporation exceeds inputs from precipitation and surface flows. The fluctuating water levels of terminal lakes are principally controlled by the balance between precipitation and evaporation within the watersheds of terminal basins (Hely et al. 1966, Smith and Street-Perrot 1983). Mean annual precipitation in most of the Salton Sea watershed is typically less than five inches, with areas near the Sea receiving less than three inches (National Weather Service 2022, Hegewisch and Abatzoglou 2021). The region is dry essentially year-round with precipitation typically confined to the winter months (Comrie and Glenn 1998, Hegewisch and Abatzoglou 2021). Normal annual evaporation at the Salton Sea is approximately 69 inches, making evaporation the largest component of the precipitation-evaporation water balance (Hely et al. 1966, CIMIS 2022). The United States Geological Survey (USGS) gauge elevation data indicate that the Salton Sea fluctuates on an intra-annual basis, likely as a result of changes in the precipitation-evaporation water balance and agricultural return flows.

Another factor affecting the Sea’s elevation is the cessation of Salton Sea mitigation water in 2017. The California State Water Resources Control Board Order for the QSA required IID to deliver mitigation water to the Salton Sea for a period of 15 years, until the end of 2017. The primary purpose of the mitigation water was to avoid salinity impacts to the Sea specifically affecting fish and wildlife. A secondary effect of the mitigation water was postponing the recession of the Sea. The State of California was to develop a Salton Sea restoration plan during that 15-year period, such that implementation of restoration activities would be underway prior to the cessation of mitigation water in 2017.
FIGURE 1. SALTON SEA ELEVATIONS OVER TIME (BLUE LINE)

The increase in frequency of water level observations (black dots) after 1989 is due to the installation of USGS gauge station #10254005 (Data pre-1989: IID 2002; data post-1989: USGS 2022).
2 2022 PLAYA EXPOSURE ESTIMATE

This section includes the methods, results, and discussion for the end-of-year 2022 Salton Sea playa exposure estimate and playa surface classification.

2.1 METHODS

2.1.1 PLAYA EXPOSURE

Playa exposure analysis is completed on an annual basis, at the end of each year when the elevation of the Sea is at the lowest point of its hydrological cycle (Figure 2). Conducting the analysis during this timeframe ensures that for any given year, the maximum extent of exposed playa is captured. The methods used to map actual playa exposure employ a combination of USGS gauge elevation data, satellite imagery, and high-resolution bathymetric data. Once the Salton Sea’s annual low-stand is identified from the USGS gauge elevation data, a cloud-free Sentinel 2 image collected as close as possible to the date of the lowstand is downloaded (Copernicus 2022). The Copernicus Sentinel-2 mission is managed by the European Space Agency (ESA) to monitor variation of Earth’s surface conditions. The mission comprises a constellation of two polar-orbiting satellites phased at 180˚ to each other, which results in a high re-visit time of 5 days (10 days at the equator with one satellite1). End-of-year 2022 playa exposure was estimated using a Sentinel-2B satellite image collected on November 26, 2022.

Next, the Modified Normalized Difference Water Index (MNDWI) was calculated from the Sentinel data. The MNDWI is one of the most utilized techniques to map surface water (Xu 2006, Feyisa et al. 2014, Zhang et al. 2011, Duan and Bastiaanssen 2013, Hui et al. 2008). The MNDWI is designed to effectively enhance open water features in imagery using green and short-wave infrared (SWIR) bands (Xu 2006, Du et al. 2016).

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MNDWI = \frac{\text{Green}-\text{SWIR}}{\text{Green}+\text{SWIR}}
\]

A threshold was then applied to the MNDWI image to identify each pixel as land or water (Xu 2006). A simple threshold value of 0 can be used to extract water features from an image, but it is common and often necessary to improve the accuracy of the extraction by adjusting the threshold to account for atmospheric absorption and lake water quality (Xu 2006, Ji et al. 2009, Duan and Bastiaanssen 2013). The threshold applied was determined by evaluating pixel values along a portion of the Salton Sea’s shoreline with a sharp contrast between the land and sea. A threshold of 0.18 was found to best isolate the water body and was applied in this analysis. This threshold is consistent with other MNDWI thresholds optimized and applied to specific sites by Feyisa et al. 2014 (0.005-0.6), Hui et al. 2008 (0.25-0.45), and Duan and Bastiaanssen 2013 (0-0.1). Bathymetric data supplemented this spectral approach on portions of playa experiencing extensive sheet flow at the outlet of drains.

The end-of-year 2002 shoreline (prior to the start of the conserved water transfer) serves as the baseline from which subsequent years are compared (IID 2016). The approach used to extract the end-of-year 2002

1 https://sentinel.esa.int/web/sentinel/missions/sentinel-2
shoreline from a Landsat 5 satellite image collected on December 27, 2002, is consistent with the methodology used to extract the current shoreline. Therefore, exposed playa for end-of-year 2022 is defined as the total area of exposed land between the former Salton Sea shoreline at the end of 2002 and the shoreline at the end of 2022.

**Figure 2. Salton Sea Elevation (blue line) Versus Playa Exposure Satellite Imagery Analysis Dates (green dots)**

![Salton Sea Elevation Graph](image)

### 2.1.2 Playa Surface Classification

After establishing the playa domain, a classification model was then applied to partition the exposed playa into three classes: “open playa,” “small pools, drain water, and sheet flow,” and “playa vegetation.” High-resolution Pleiades satellite imagery collected on November 10, 2022, was used to classify the exposed playa. Classification of remotely sensed image data is one of the most studied topics in the field of remote sensing due to its wide range of ecological, environmental, and socioeconomic applications (Lu and Weng 2007, Li et al. 2014, Li et al. 2016). The technique often involves statistical modeling processes to predict categorical response variables. Several approaches for image classification are available, ranging from relatively simple thresholds based on spectral index values (for instance, using MNDWI for water body extraction; Xu 2006) to more sophisticated multivariate methods based on machine learning (Li et al. 2016). Selection of the appropriate statistical classification approach often boils down to choosing...
between methods that favor the interpretability of the modeling process at the expense of predictive accuracy (e.g., regression, thresholds, discriminant function analysis), or more complex methods that tend to provide better predictive accuracy (and reliability) by sacrificing some interpretability of the model's process (Breiman 2001). The selection of the best approach for a specific application ultimately depends on the end-user requirements and resources available to perform the analysis.

A pixel-based machine learning approach was selected to account for the complexity and scale of the playa surface classification. This pixel-based approach considers the image pixel as the basic unit of analysis, and this technique has been developed and used for the last few decades (Li et al. 2014, Lu and Weng 2007, Gallego 2004). With this approach, each pixel is assigned a single class based on the spectral information captured by the pixel. A Normalized Difference Vegetation Index (NDVI) was derived and included as a variable alongside the red, green, blue, and near infrared bands (NIR). The NDVI is one of the most utilized techniques to delineate and monitor vegetation (Tucker 1979, Tucker et al. 2005, Xue and Baofeng 2017, Albarakat and Lakshmi 2019).

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\text{NDVI} = \frac{(\text{NIR}-\text{Red})}{(\text{NIR}+\text{Red})}
\]

In recent years, machine learning algorithms have been made available by the open-source H2O platform (Cook 2016, https://www.h2o.ai/) for straightforward access and implementation. H2O enables the implementation of various machine learning, deep learning, and artificial intelligence algorithms (Cook 2016, Aiello et al. 2015, Candel and LeDell 2020, LeDell and Poirier 2020), including Gradient Boosting Machine (GBM), Distributed Random Forest (DRF), and Deep Learning (Neural Networks) algorithms. This platform has been utilized in previous land surface mapping and monitoring studies with remote sensing data (Abdi 2020, Burchfield et al. 2016, Cheng et al. 2022).

H2O’s Automatic Machine Learning (AutoML) framework was implemented because it automatically evaluates and optimizes multiple learning algorithms (e.g., GBM, DRF, Neural Networks) at once to attain better predictive performance. AutoML identified a GBM model as the top performing model for the playa surface classification. GBM is a forward-learning ensemble learning method that builds regression trees to generate increasingly refined predictions. GBM models sequentially build regression trees in parallel, sequentially combining weak models to reduce the residual error of the previous model to create a powerful ensemble model (Singh 2018). These models are relatively easy to implement, provide readily interpretable model diagnostic information (e.g., variable importance metrics), and have been successfully applied in various land use/land cover mapping projects (e.g., Lacoste et al. 2011, Georganos et al. 2018, Abdi 2020, Forkuo et al. 2018, Heryadi and Miranda 2020, Cheng et al 2022).

The training dataset features were scaled using a standard scaling technique. This means that for each variable, the mean of the variable was subtracted over the entire dataset and divided by the standard deviation of that variable over the entire dataset. This ensures that any one variable is not dominating the classification by having each variable have a mean of zero and standard deviation of one. Minority classes within the training dataset were oversampled to balance the class distribution. Models were instructed to stop after one round to reduce processing time spent with diminishing returns. To avoid overfitting, each model’s performance was assessed against an internal and external dataset (Lacoste et al. 2011).
The internal dataset was the training dataset used to predict the model while the external dataset consisted of an independent validation dataset randomly partitioned from the original training dataset prior to the model run. A total of 11,700 training data points randomly sampled within photo-interpretive polygons (in areas of distinct playa surface classes) were used to develop the classification model.

2.2 RESULTS AND DISCUSSION

2.2.1 PLAYA EXPOSURE

Analysis results identified 30,569 acres of exposed playa. This represents an increase of approximately 2,880 acres from the 27,689 acres mapped at the end of 2021. Over the five years prior to 2022, new playa exposure increased incrementally following the cessation of mitigation water in 2017, reaching 3,006 new acres between 2018 and 2019 (IID 2021). The annual rate of new playa exposure fell to 1,672 in 2020 before increasing to 2,100 in 2021 and increasing further to 2,880 in 2022 (IID 2022). Figure 3 shows actual playa exposure levels from 2003 through 2022.

FIGURE 3. ACTUAL PLAYA EXPOSURE FROM 2003 THROUGH 2022

The Salton Sea's unique bathymetry produces an uneven distribution of exposed playa. The Salton Sea is composed of two sub-basins in the north and south. Current and anticipated exposure is higher in the
relatively larger, shallower southern sub-basin. Regions with shallower slopes and higher exposure rates include the three prograding deltas of the Whitewater, Alamo, and New Rivers; as well as the relatively large and active alluvial fans that drain the Tule and San Felipe washes. Regions that are less susceptible to exposure include the alluvial margins that flank the western and eastern margins of the relatively deeper northern sub-basin, the portion of the playa that extends along the western flank of the anticlinal Durmid Hill north of Bombay Beach (Jänecke et al. 2018), and the stretch of playa adjacent to the gently convex structure situated between the Tule and San Felipe fans (Haff and Presti 1995).

2.2.2 Playa Surface Classification

To provide additional context to exposed playa estimates, the playa was subdivided into three general classes (open playa; small pools, drain water, and sheet flow; and playa vegetation) (Figure 4). The GBM model used to map playa surface classes identified NDVI as the most influential predictor. Table 1 and Table 2 show a breakdown of results for each playa surface class predicted from the internal training data and external validation data. All correct classifications are shown in the gray diagonal of the table. Errors between the training data and predicted data for each class are in the right-hand columns.

The confusion matrices indicate that the majority of training and validation data were classified correctly. The statistics are consistent and the errors were lower when compared with similar studies (Fu et al. 2017, Berhan et al. 2018; Feng et al. 2019). Fu et al. (2017) leveraged a pixel-based RF algorithm to map wetland vegetation with an overall accuracy of >80%. The Random Forest (RF) model used by Berharne et al. (2018) to map wetlands in the Selenga River Delta of Lake Baikal, Russia, achieved an overall accuracy of >81%. Feng et al. (2019) utilized a multibranch convolutional neural network to generate a land cover map of the Yellow River Delta in China and achieved an overall accuracy of 93.78%.

**Table 1. Internal Confusion Matrix for Playa Surface Classes**

<table>
<thead>
<tr>
<th>Predicted Data Classification</th>
<th>Open Playa</th>
<th>Small Pools, Drain Water, and Sheet Flow</th>
<th>Playa Vegetation</th>
<th>Total</th>
<th>Error %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small Pools, Drain Water, and Sheet Flow</td>
<td>3,384</td>
<td>0</td>
<td>1</td>
<td>3,385</td>
<td>0.03</td>
</tr>
<tr>
<td>Open Playa</td>
<td>0</td>
<td>3,359</td>
<td>0</td>
<td>3,359</td>
<td>0.00</td>
</tr>
<tr>
<td>Playa Vegetation</td>
<td>0</td>
<td>0</td>
<td>3,387</td>
<td>3,387</td>
<td>0.00</td>
</tr>
</tbody>
</table>

0.01
Water bodies on the exposed playa are not a dominant feature, but they were mapped to define small pools, drains, and sheet flow commonly found in small depressions at or near the confluence of the direct drains and/or rivers to the Sea. Open playa comprises bare playa and sparse/senescent vegetation because some areas of sparse vegetation (e.g., hedgerows implemented for dust control) may not be identified as part of the playa exposure analysis due to the resolution of the Pleiades imagery (2-m resolution). Results demonstrated that the open playa class increased from the previous year by approximately 2,231 acres to 22,169; small pools, drain water, and sheet flow increased by approximately 95 acres to 662; and playa vegetation increased by approximately 554 acres to 7,738 (Figure 4).

Vegetation implemented for dust control generally occurred in hedgerows (e.g., in furrows with a width of ~10 feet), except for natural vegetation enhancements near existing dust control areas and dense vegetation in the Alamo North project area. Approximately 3,730 acres of dust mitigation projects have been implemented around the Sea. This includes approximately 1,290 acres of surface roughening, approximately 860 acres of surface roughening with vegetation-based dust control, and 1,580 acres of temporary surface roughening in the State’s Species Conservation Habitat Project Area. Actual acreages of surface roughening may be reduced due to expansion of natural vegetation at the time of implementation. Significant acres of recent natural vegetation enhancements were also observed near existing dust control areas. A detailed vegetation assessment, which includes vegetation implemented for dust control, was conducted as part of quarterly performance monitoring activities using the Light Detection and Ranging (LiDAR) remote sensing method. This approach is more appropriate for quantifying sparse vegetation in hedgerows (IID 2020b).
The Salton Sea Analysis (SALSA) model is described below in Section 3.
3 Actual Playa Exposure Vs. Projected Playa Exposure

The timing and location of future playa exposure is a function of the hydrologic response of the Salton Sea to external forces, such as inflows, salt loads, and evaporation rates. The Salton Sea Accounting Model (SSAM) was originally developed by the United States Bureau of Reclamation to simulate the effects of the water transfers under the QSA on Salton Sea surface elevation and salinity. In 2006, the hydrologic modeling framework was revised to incorporate additional data and water balance improvements, and to add flexibility to the model. The updated model is called the Salton Sea Analysis model (or SALSA model), developed for the Programmatic Environmental Impact Report (PEIR) for the Salton Sea Ecosystem Restoration Program, which was prepared under the direction of the California Department of Water Resources and the California Department of Fish and Wildlife\(^2\) on behalf of the Natural Resources Agency.\(^3\) The SALSA model was updated further in 2018, and results were published by IID (IID 2018).

Projected playa exposure using the “median” model run from the SALSA2 model was compared to actual playa exposure from satellite imagery. The difference in acreage between actual playa exposure and the projected playa exposure from SALSA2 is higher than in previous years. The difference between actual playa exposure versus projected playa exposure in 2018 was relatively close and well within the “prediction envelope” of the 25th and 75th percentiles predicted by SALSA2 (Figure 5). In 2022, the difference between 42,407 predicted acres and the 30,569 actual acres of exposed playa has grown to 11,838. This discrepancy puts actual playa exposure below the 5th percentile (35,873 acres) predicted by SALSA2 for 2022.

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\(^2\) Formerly the California Department of Fish and Game
\(^3\) Formerly the California Resources Agency
FIGURE 5. ACTUAL PLAYA EXPOSURE FROM SATELLITE IMAGERY VERSUS SALSA2 MODEL PROJECTED PLAYA EXPOSURE

4 REFERENCES


