Mapping Wastewater Odor Impacts: A Spatial Analysis of Odor Complaint Data

MGIS 596B CAPSTONE PROJECT REPORT

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Abstract

Odors emitted from sewers and treatment plants can be a nuisance in their neighborhood and a challenge for wastewater agencies. Understanding the spatial distribution of historic odor complaints within the service area can help plant operators and engineers identify populations at risk for wastewater odor impacts, and focus outreach efforts in communities where odor complaints occur or may occur in the future.

This project analyzed approximately 611 odor complaints collected by the Orange County Sanitation District between 2012 and 2018. Calls were determined to be clustered based on G, F, K and pair correlation functions in R.

The results from the point pattern analysis and geospatial methods were used to produce an 'odor impact zone' within the service area, outlining the at-risk population (35% of the total 2.5 million residents). The impact zone covers 86% of the collected odor complaints and 96% of complaints related to District facility odors. With awareness of this impact zone, operators can identify systemic trouble spots in the collection system, screen future odor calls for odors originating from their wastewater facilities, and assess the effects of current odor mitigation techniques at the treatment plants.

1. Introduction

Understanding the impacts of odors coming from wastewater facilities is a difficult and complex problem. Odors can be produced in a collection system or at treatment plants, where sewage is handled, causing an ongoing nuisance to in the surrounding community. Procedures for mitigating odors often begin in response to complaints from residents. In this paper GIS-based tools and statistical software are used to analyze historical complaint data reported to the Orange County Sanitation District facilities. The focus of this project is an analysis of the spatial distribution of odor-related calls received by OCSD from 2012-2017 to determine the extent of potential wastewater odor impacts in the service area.

The results from this project will allow operators to evaluate odor mitigation methods based on collected odor observations and make timely investigations of complaints. Understanding the nature and spatial distribution of odor impacts will help wastewater agencies focus odor control efforts on the most affected populations and build better community relationships through proactive solutions.

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2. Background

The Orange County Sanitation District (OCSD or District) is a regional wastewater agency located in Orange County, California. The District manages and treats sewage collected from over 2.5 million people in the northern and central parts of Orange County. The District's Service Area covers 21 cities, including Newport Beach, Huntington Beach and Anaheim. Local sewers in these communities transport wastewater to a regional network of 400 miles of sewer lines and includes 4,640 manholes that the District owns and maintains. The District's facilities also include 15 pump stations and two wastewater treatment plants (WWTPs). Reclamation Plant No. 1 is located in Fountain Valley and Treatment Plant No. 2 is located in Huntington Beach. Both plants treat approximately 100 million gallons per day. The District's service area and two treatment plants are shown in Figure 1.



Figure 1. OCSD Service Area and treatment plants. (Esri World Light Gray Reference, 2017). All rights reserved. Reproduced for educational purposes only.

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3. Odor Complaint Data

The Control Center at Reclamation Plant No. 1 receives calls from residents within the service area for issues related to the plant or sewer facilities (e.g. spills, odors, noise, construction). Between April 2012 and February 2018, approximately 611 odor-related calls were logged. The information collected during the call included: the caller's name and address, a description of the problem, the location of the odor incident and any major cross streets. The Call Center also categorized the call based on whether it was in the plant or collection system, the type of odor (sewer, chemical, rotten eggs), the cause of the odor (if known), whether or not OCSD was the source, and the status of response actions. In some cases the wind speed, wind direction, and temperature at the time of the call were noted.

For analysis with GIS software, the calls were geocoded based on the street address listed and saved in a point feature class. Approximately 50% of the records were matched through the automated geocoding. The remaining points were geocoded manually using the intersections or customer descriptions recorded during the call.

Next, the original Odor Type attribute field included some categories of odor smells that were repetitive or too specific (1-2 records). These categories were reviewed and compared to the original customer description for consistency. Most of the records were found to match the caller's descriptions; however, there were instances where the category differed from the description. To analyze all the reported odors in a consistent and efficient manner, the calls were reclassified into a predefined list of odor categories. The wastewater odor categories applied in this project were derived from the results of a study done to develop an odor classification scheme (Burlingame et al., 2004; Suffet et al., 2009). The study defined 10 categories of compost odors produced by plants that treat wastewater. Table 1 is a list of these categories. Additional categories were made for non-wastewater and unspecified odors.

Figure 2 is a map of the odor calls plotted on OCSD's service area. Figure 3 is a breakdown of total odor calls by odor category. A large number of calls appear to occur in the western half of the service area, particularly the southwest. Groups of calls were located in Tustin, on the east side, in Yorba Linda to the north, and in Newport Beach along the coast. A majority of the 611 calls, 392 (64.2%), were categorized as Fecal/Sewery, 70 (11.5%) were sulfide/cabbage, and 50 (8.2%) were bleach/burnt/chemical.

	Wastewater Odor Category	Odor Descriptor
1	Ammonia/Fishy	Ammonia
2	Earthy/Moldy/Musty	Earthy/musty, moldy
3	Fecal/Sewery	Fecal, manure, sewery
4	Fragrant/Fruity	Soapy, fruity, citrusy
5	Grassy/Woody	Grass, woody, hay
6	Medicinal/Alcohol	Medicinal, alcohol
7	Oxidant/Chlorinous	Chlorine
8	Rancid/Putrid	Sour milk, rancid, putrid, decayed
9	Solventy/Hydrocarbon	Burnt smoky, rubbery, chemical
10	Sulfide/Cabbage/Garlic	Rotten eggs, rotten cabbage, decaying vegetation

Table 1. Categories from Wastewater Odor Wheel (Suffet et al., 2004)

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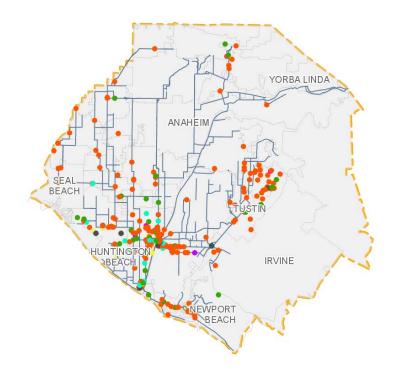


Figure 2. Distribution of odor complaints received by OCSD between 2012 and 2018. ©2018 ESRI All rights reserved. For educational purposes only.

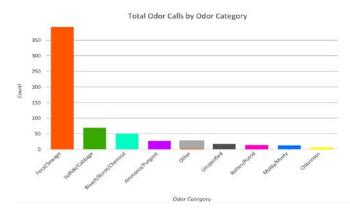


Figure 3. Total odor complaints by odor category for calls between 2012 and 2018 ©2018 ESRI All rights reserved. For educational purposes only.

4. Odor Complaint Analysis

The aim of this project was to further define the extent of odor impacts due to wastewater facilities. As shown in Figure 2, the spatial distribution of calls is not evenly spaced across the service area; a higher number of calls occur in the southwest region near the plants, and higher concentrations of calls appear in groups to the east, north and south along the coast. To examine the degree of clustering as well as the size and spacing of clusters, point pattern analysis with several distance-based functions in R was performed. To determine the locations of clusters, two geospatial methods – spatial scanning statistics in SaTScan and kernel density estimation using ArcGIS – were applied using the call data.

Clusters of odor calls in the vicinity of both OCSD plants were examined and compared to the results of previously modeled nuisance extents for hydrogen sulfide (H_2S) to estimate the extent of impacts due to treatment plant odors. For calls related to collection system odors, the distance between the caller and the problem manhole or sewer were reviewed and used to determine an approximate buffer zone around OCSD's sewer and pump stations. Combined with the estimated odor impact extent around the plants, an odor impact zone was produced and compared to the location of the historical odor complaints.

4.1 Point Pattern Analysis Using R

To assess the point pattern of the 611 calls in a statistical manner, a number of distance-based functions were applied to their spatial distribution. This was done using the spatial statistics package available in R. Figure 4 shows the *G*-function, or refined nearest neighbor function, for the odor call data. The graph is a cumulative distribution of distances between a call and the next closest call. The sharp slope at distances below 20 feet indicates a pattern of neighboring calls in this range. Approximately 60% of the nearest neighbor distances were under 20 feet.

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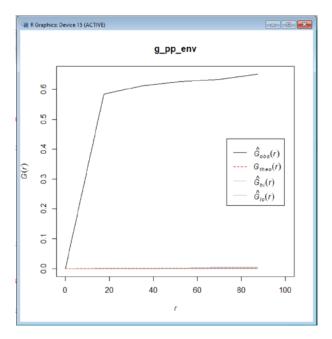
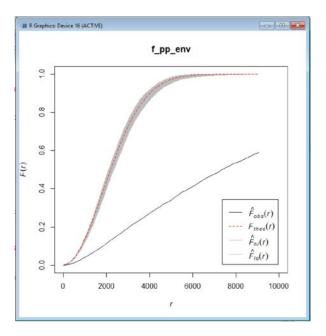


Figure 4. G-function for odor call data. ©2018 The R Foundation for Statistical Computing. All rights reserved. For educational purposes only.

Figure 5 shows the *F*-function for the call data (black line). This differs from the *G*-function in that the plot shows the distances from a call to randomly selected points in the region. The F-function is indicative of how far away calls are from random points in the study area. An evenly-spaced pattern would have more random points fairly close to a call, creating a higher slope for short distances. The slope of the *F*-function for the call data is gradual, and does not rise rapidly at any distances below 10,000 feet. There are empty spaces in to the north and in the southeast regions of the service area, indicating very long distances to the nearest odor call.



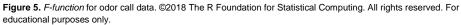


Figure 6 shows the *K*-function for the call data. The *K*-function is based on the number of events (calls) within a circle of radius d around an event. If the point pattern were evenly spaced, the function would have a consistent, straight slope. The graph in Figure 6, however, has two bends. At the first arrow, the bend indicates a cluster size around 2000-2200 feet. The second arrow shows the upper range of cluster separation - around 18,000 feet. The graph is not completely horizontal in the 2000 to 18000 range, so there appears to be some clustering, but not a strong degree.

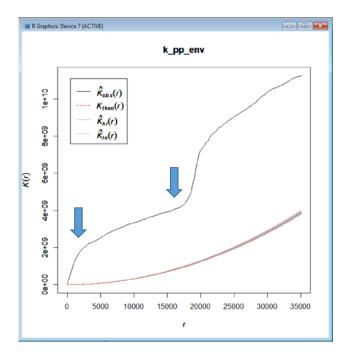


Figure 6. K-function for odor call data. ©2018 The R Foundation for Statistical Computing. All rights reserved. For educational purposes only.

The graph in Figure 7 shows the *pair correlation function* for the calls. This function focuses on the separation distance of any pair of points in the pattern. The graph shows many pairs separated at distances below 5000 feet, many of them below 3000 feet. As illustrated later in Figures 16 and 17, this could be due to the spacing of calls within clusters, mainly within the clusters the two plants, which account for roughly 61% of the total calls. There is also a large number of pairs separated at 19,000 feet. The high number of points at the larger separation distance could be due to the number of calls clustered around each treatment plant, with the plants located approximately 19,000 feet apart.

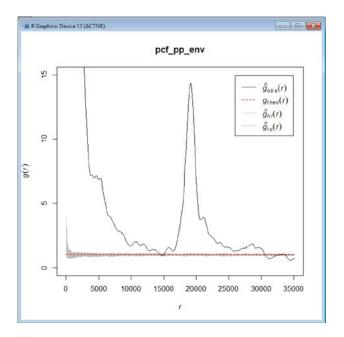


Figure 7. Pair correlation function for odor call data. ©2018 The R Foundation for Statistical Computing. All rights reserved. For educational purposes only.

Based on the four functions, it appears that the call pattern consists of many calls in close proximity to each other, most having a nearest neighbor less than 20 feet away. There are empty spaces in overall distribution of odor calls, and clusters specific regions of the service area, such as the west side. Of the clusters that are present, the K function indicates they are around 2200 feet maximum and spaced 19,000 feet apart. Many pairs of points appear to be spaced 3000 feet apart or less, yet there is also significant separation distances at 19,000 feet. While the information is useful, it can be difficult to interpret without knowing the location or intensity of the clusters. So a kernel density estimation was performed to examine these first-order effects.

4.2 First-Order Effects Using Kernel Density Estimation

A kernel density estimation was performed to investigate first-order effects in the call pattern density across the service area. Kernel density methods calculate the density for each point in the entire region by counting the number of points in a neighborhood (specified by the search radius). Given a service area of 478 square miles and 611 calls, the estimated overall intensity in this project is 1.27 calls per square mile.

The kernel density method was applied using the *kernel density tool* in ArcGIS Pro. This method estimates the density of points (calls) at a given location based on the number of points within a given proximity of that point. The area, or 'neighborhood' of proximity is defined by the search radius, and calls closer to a specified point are assigned a larger weight in the kernel function at that point. The kernel density method is very scale-dependent, so a sensitivity analysis was performed to determine an appropriate search radius for this project. If the value is too large, the result is too generalized, making local patterns difficult to discern. If the radius is too small, the focus is on small clusters which are similar to the actual point pattern.

The results from the *K*-function indicated cluster sizes around 2000-2200 feet. For this project, a search radius of ½ mile, or 2640 feet, was chosen as a proper 'neighborhood' size for analysis. Figure 8 shows the kernel density output raster for the service area. Contours were generated from the raster values.

The highest call intensity occurred near both treatment plants, where the call density exceeded 100 calls per square mile. There is also some initial cluster development in selected areas of the map in Figure 8: Tustin, Seal Beach, Newport Beach, and Huntington Beach. However, the call intensity is much less: most of the kernel density in these clusters were 30 calls per square mile or less. A kernel density up to 45 calls per square mile was found in only two clusters. Of the 611 calls, 374 calls (61%) are located within one mile of the treatment plants. The distance between the two plant clusters in Figure 8 is approximately 19,000 feet, corresponding to the larger separation distance in the *pair correlation function* result. The other clusters are smaller in size, less intense and spaced far apart. Overall, the data shows isolated clustering outside of the plants, but not to a strong degree.

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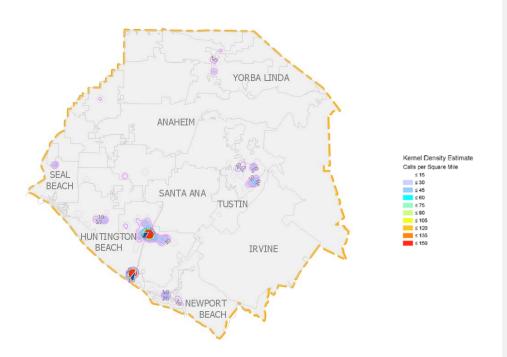


Figure 8. Kernel density estimates for odor calls between 2012 and 2018. ©2018 ESRI All rights reserved. For educational purposes only.

4.3 Cluster Detection With SaTScan

To properly examine second-degree effects of calls, or local clustering, the background population was taken into account. This was done using SaTScan, a software used for analyzing spatial and temporal data and detecting clusters using scan statistics. Spatial scanning statistics involves placing a circular scanning window on the map of data and evaluating the count data (odor calls), population, and any other covariates inside the window. The window moves systematically across a grid based on input coordinates, and varies in size between 0 and an upper limit. Each window size/location combination is a potential cluster, with an assigned p-value. A low p-value (i.e. 0.01) indicates a very low probability that the spatial pattern of calls within the window was generated randomly.

The SaTScan software has different probability models depending on the application of scan statistics. For this project, the discrete Poisson model was used. The occurrence of calls was assumed to have a Poisson distribution – the expected number of calls and the at-risk population count are directly proportional. The analysis performed here was a purely spatial; no temporal factors were incorporated.

The input data for SaTScan consists of 3 input files: a case file (odor calls), a population file, and a coordinates file. To create the input files, a polygon shapefile of 462 census tract boundaries was created. ArcGIS was used to perform a spatial join and determine the count of odor calls within each census tract. The cluster detection analysis focused on total number of odor calls, regardless of odor type.

The population data used in this project was taken from the American Community Survey 5-Year Estimates for 2012-2016. This included U.S. Census population data at the tract level for Orange County, California. A spatial join was used to join the total population (male and female, all ages) for each tract to the polygon shapefile.

Latitude and longitude coordinates for centroids of the 462 census tracts in the polygon shapefile were also calculated using ArcGIS. The information was used to create the input coordinates file (the series of points for the scanning window). The set of points used by SaTScan for this project is shown in Figure 9.

The SaTScan model was run with the input files and the analysis parameters previously described. The maximum spatial cluster size was set to 25% of the at-risk population. Smaller clusters are also evaluated in the model run. To bolster the statistical analysis, the number of Monte Carlo replications was set to 9999.

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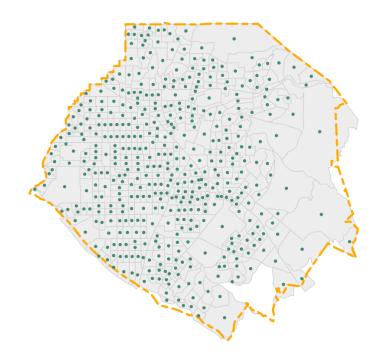


Figure 9. Census tracts and centroids within OCSD service area. (US Census Bureau, 2016) ©2018 ESRI All rights reserved. For educational purposes only.

4.4 SaTScan Results

Figure 10 shows the results of the SaTScan model run. Calls regarding odors from OCSD assets are shown as darker dots with black outlines. The SaTScan model calculated 24 cases per 100,000 people for the entire service area.

Two statistically significant clusters were identified: Cluster 1 in the Tustin area and Cluster 2 around the two wastewater treatment plants. Cluster 1 was calculated to have 272.8 cases per 100,000 people and a p-value less than 1E-17. Cluster 2 was calculated to have 148.7 cases per 100,000 people and a p-value of 1.3E-14. The low p-values indicate the two observed call clusters are unlikely to be generated by a random spatial process.

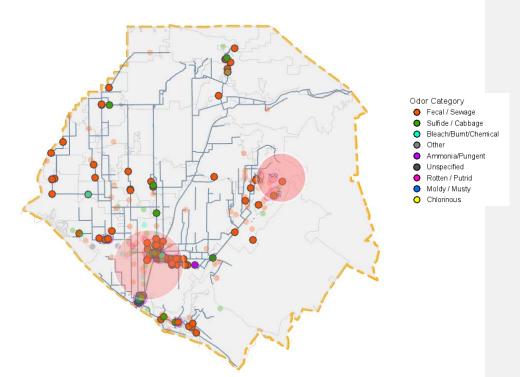


Figure 10. Odor call cluster results using SaTScan and sewage collection system. ©2018 ESRI All rights reserved. For educational purposes only.

4.5 SaTScan Cluster 1

Figure 11 shows the two SaTScan clusters overlaid on the Census tract data. Based on a population of 2.5 million people and 611 odor-related calls, an incident rate for the entire service area was estimated as 0.02%. A close-up of Cluster 1 is shown in Figure 12. The plant properties and sewers are shown in blue. Most of the 391 calls are split into two sub-clusters – one near each treatment plant. Calls near Plant 1 also extend along the sewers to the north and east of the plant, possibly due to odors from manholes along these trunklines. The calls near Plant 2 appear to be concentrated in a small neighborhood on the northwest side of the plant.

The total number of calls by category for this cluster is shown in Figure 13. There were 391 calls in this region. Most of them, 228 (58%) were fecal/sewage odors. Of the remaining calls, 46

(12%) were sulfide cabbage and 40 (10%) were in the bleach/sulfide/chemical category. 234 calls were found to be OCSD-related odors, 143 were non-OCSD odors, and 11 were undetermined.

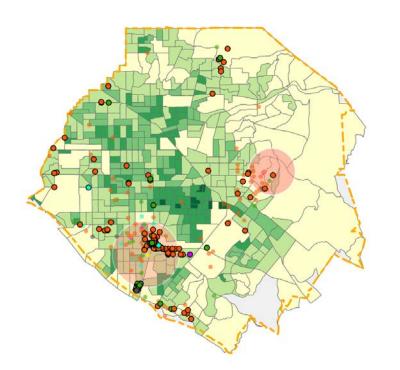


Figure 11. SatScan cluster results and population density for Census tracts in OCSD service area. ©2018 ESRI All rights reserved. For educational purposes only.

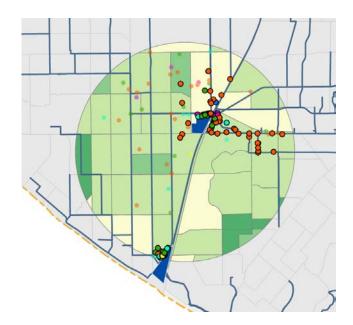


Figure 12. Odor calls and population density in Cluster 2 of SaTScan result. ©2018 ESRI All rights reserved. For educational purposes only.

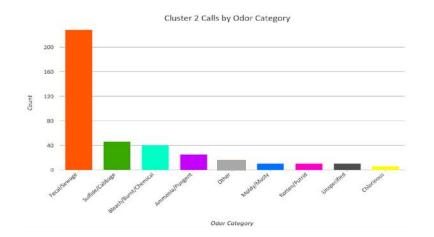


Figure 13. Odor categories for calls in SaTScan Cluster 2. ©2018 ESRI All rights reserved. For educational purposes only.

4.6 SaTScan Cluster 2

A detailed map of Cluster 2 is shown in Figure 14 with the sewer lines. Smaller diameter sewers are in lighter blue. This cluster is located in the city of Tustin, in an area with a lower population density. There were 37 total calls in this cluster. There does not appear to be a distinct pattern in the distribution of the calls, other than their proximity to sewers. Figure 15 is a breakdown of calls by odor. The majority of calls, 30, were sewage odors. Only 3 of the calls (all sewage odors) were found to be related to OCSD assets. This may indicate other sources of sewage odors in the area– drainage ditches, construction work, storm drains, etc – that were presumed to come from the collection system.

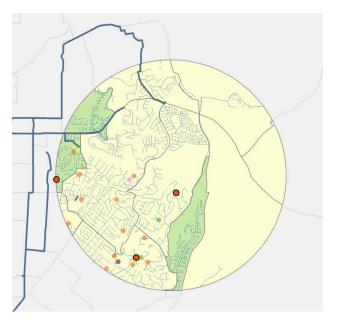


Figure 14. Odor calls and population density in Cluster 1 of SaTScan result. ©2018 ESRI All rights reserved. For educational purposes only.

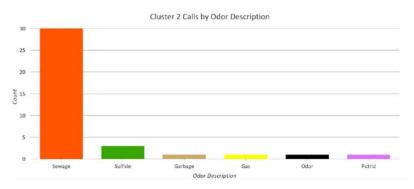


Figure 15. Odor categories for calls in SaTScan Cluster 1. ©2018 ESRI All rights reserved. For educational purposes only.

4.7 Plant Odors

Following the odor characterization study of plant odors through chemical and sensory analysis done by UCLA (Suffet et al., 2014; Suffet et al., 2015), the District hired CH2M Hill to perform air dispersion modeling, a common method for simulating the dispersion of air pollutants. The AERMOD model was chosen for this effort. The purpose of the modeling task was to assess the extent and frequency of modeled concentrations above odor concentration thresholds.

The model was run with plant facilities as of 2016 as a baseline condition. The output from the model is a concentration value at each point of a receptor grid. From the grid of concentrations, lines for specific concentrations, known as isopleths, were generated using ArcGIS. Figure 16 shows the distribution of odor calls in the vicinity of OCSD's Reclamation Plant No. 1. The predicted nuisance level isopleth for H₂S (0.0013 ppm) described in the final report (CH2M Hill Engineers, Inc., 2017) is shown in green. The output contours from the kernel density results are shown in purple.

The modeled isopleth shows the extent of nuisance odors varies approximately 2400-6000 feet from the plant. Approximately 235 odor calls are located within this extent. Most of the historic odor calls describing a sulfur (rotten-egg) odor from the OCSD treatment plant (shown as dark green dots) occurred at or within 1000 feet of the plant. There were also several sewage/fecal odor calls from OCSD assets that did occur within the boundary of the H₂S nuisance isopleth. These odors may have consisted of H₂S, along with other (stronger) odorants.

Table 2 shows a breakdown of the Plant 1 cluster by distance band. About 229 calls were located within a 1 mile buffer of Plant 1. Of these 229 calls, 200 (87.3%) were within ½ mile of the plant and 160 (69.9%) were within 1000 feet. Many of the calls appear to come from locations at the north and east sides of the plant, or along the incoming sewers.

The density contours are centered on a neighborhood at the northeast corner of the plant. This may be due to prevailing winds coming from the east-southeast, as well as the all the regional trunklines entering the headwork facilities at this corner of the plant.

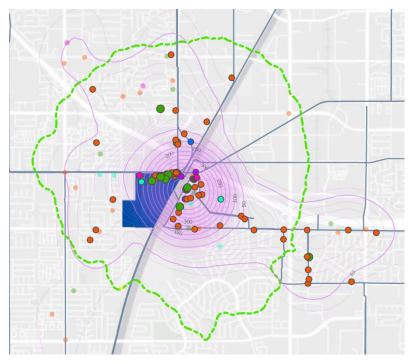


Figure 16. Modeled H_2S isopleth and density contours for Plant 1 odor calls. (Esri World Light Gray Reference, 2018). All rights reserved. For educational purposes only.

Plant 1 Buffer	Number of calls	Percentage of calls in buffer
1 mile	229	100%
½ mile	200	87.3%
1000 feet	160	69.9%
500 feet	74	32.3%

Table 2. Total calls in Plant 1 cluster by distance band. (Saqui, 2018)

The distribution of odor calls in the vicinity of OCSD's Treatment Plant No. 2 is shown in Figure 17. The predicted nuisance level isopleth for H_2S is shown in green. At Plant 2, all of the odor calls were located on the northwest side of the plant. The eastern side of the plant is bordered by the Santa Ana River, a park and open field areas. There are no residential or industrial areas immediately east of the plant. The extent of the H_2S isopleth ranges 3000 - 5000 feet away from Plant 2. Approximately 143 calls were within this isopleth extent. Almost all of the plant-related calls, including H_2S odors, occurred within $\frac{1}{2}$ mile of the plant boundary.

Table 3 is a breakdown of the Plant 2 cluster by distance band. About 145 calls were within 1 mile of Plant 2. Of these 145 calls, 143 (98.6%) are within a ½ mile and 137 (94.5%) are within 1000 feet. The Plant 2 cluster is more compact than Plant 1, and is limited the northwest side of the plant.

The kernel density contours center around a neighborhood north of the plant. The headworks of Plant 2 are located in the middle of the property, however, residents may be reporting odors carried by prevailing coastal winds coming from the southeast.



Figure 17. Modeled H₂S isopleth and density contours for Plant 2 odor calls. (Esri World Light Gray Reference, 2018). All rights reserved. For educational purposes only.

Plant 2 Buffer	Number of calls	Percentage of calls in buffer
1 mile	145	100%
½ mile	143	98.6%
1000 feet	137	94.5%
500 feet	123	84.8%

Table 3. Total calls in Plant 2 cluster by distance band (Saqui, 2018)

4.8 Collection System Odors

Regarding odors in the collection system, the original call data listed the manholes or sewers causing the odors for roughly 60 calls. ArcGIS was used to digitize lines representing the distance from the address of the caller to the problem manhole or sewer. Figure 18 is a histogram of these distances. A maximum distance was chosen if multiple manholes were listed. About 33 segments were under 553 feet. 46 segments (77% of the total) were under 1100 feet. A length of 1100 feet was used as an estimate of the typical distance between a caller and the potential problem asset.

This distance was used to create a buffer zone around the OCSD collection system. Additional ½ mile buffers were created around each treatment plant, based on the high percentage of calls located within this distance band. The buffers were merged and resulting odor impact zone is shown in Figure 19, with the enclosed population densities. The two treatment plant boundaries are shown in blue. The total at-risk population is 871,737 (35%). Of the 611 historic odor calls, approximately 524 (86%) of the calls are within the impact zone. Of the 324 OCSD-sourced calls, 311 (96%) are located within this zone. In 2016, a large number of local sewers (over 100 miles) were transferred to another agency for maintenance. If the buffer had included these sewers, the percentage of total calls covered would increase to 573 (93.8%).



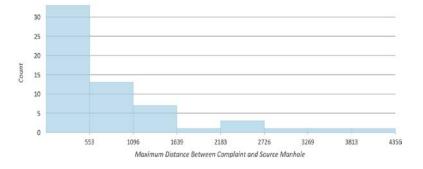


Figure 18. Histogram of distances between the location of caller and odor source. ©2018 ESRI All rights reserved. For educational purposes only.

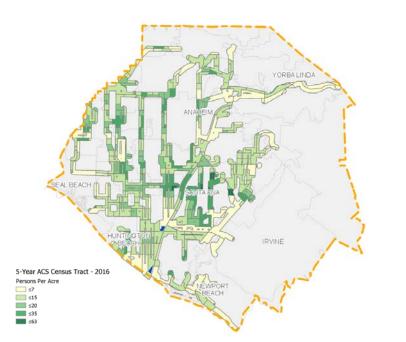


Figure 19. Odor impact zone for wastewater collection system and plants, and affected population. ©2018 ESRI All rights reserved. For educational purposes only.

5. Discussion

This project performed spatial analysis of 611 odor calls utilizing several geospatial methods and tools in ArcGIS. The F, G, K, and pair correlation functions performed in R indicate many odor calls occur in close proximity to their nearest neighbor, forming some clusters up to 2000-2200 feet in size and a cluster separation around 18,000 feet. The point pattern analysis was further described by mapping the clusters using the *kernel density function*. The highest intensity clusters were located at each of the plants, and some initial clustering in other pockets of the service area: Tustin, Newport Beach, Seal Beach, and Yorba Linda.

Including population as a factor, SaTScan was also used to detect and map clusters in the area. In addition to identifying the plant clusters, a cluster in Tustin was identified as statistically significant. SaTScan, however, did not determine the other clusters found through kernel density to be statistically significant. Similar results pointing out differences in cluster detection output using SaTScan and kernel density methods have been found in other studies, such as detection of nPCR hotspots for malaria transmission in Tanzania (Mosha et al., 2014) and clusters of leukemia cases in Ohio (Wheeler, 2007). In both studies, the kernel density method showed more local clusters while SaTScan identified fewer or no statistically significant clusters.

The identification of clusters is beneficial for wastewater operators focused on odor mitigation efforts. In the collection system, numerous and/or frequent calls in an area may point to a consistent problem with sewage flow, stemming from environmental factors or current sewer design. At the plants, understanding the spread and detection of nuisance odors can help plant operators assess the effectiveness of odor mitigation techniques as they are implemented in plant facilities. Plant odors are complex and comprised of multiple odorants. As OCSD continues to test and improve odor mitigation techniques at its facilities, there is concern that removing certain odorants in the treatment process may allow other odorants (i.e. Methyl Mercaptan) to become more prominent. This layering of odors is compared to "peeling an onion". (Suffet et al., 2015) Tracking and categorizing odor calls may help operators understand which plant odorants create nuisance smells in the neighboring communities.

Analysis of the spatial distribution of calls, around the plants and in proximity to the collection sewers supported the determination of an 'odor impact zone' around OCSD assets. This could lead to a better understanding of the at-risk population, so that outreach efforts can be proactive and efficient. Different communities may have varied tolerance levels for wastewater odors, and understanding the potential impact zone can help staff better engage with residents who may experience odors prior to a construction or sewer rehabilitation project.

An odor impact zone could assist in screening incoming odor calls as well. Of the 611 odor calls analyzed, only 324 (53%) were determined to originate from OCSD assets. Knowing if the caller's location is within the odor impact zone can help the Call Center technician gage the likelihood of OCSD as the source more efficiently, and involve other jurisdictions as needed.

With the development of mobile GIS technology such as ESRI's Survey123 application, more accurate location and time information can be collected. This could be used by staff to record odor observations in response to calls, or even record the lack of an odor, providing additional

data for analysis. Along with educational outreach on wastewater odors, this could also be a beneficial opportunity for the public to participate by reporting nuisance odors through a cost-effective and time-saving application.

6. Conclusion

As demonstrated in this paper, geospatial software and tools can be useful in describing, quantifying, and communicating the extent of historic odor impacts. Beyond a pattern of points, descriptive statistics and the output from geoprocessing tools and analysis software such as R and SaTScan can highlight point pattern trends and significant clusters of calls for further investigation. GIS-based applications can also aid in the collection of new data points, to support continued analysis of odors from wastewater facilities. Recent advancements in GIS software incorporate space-time analysis tools, wherein the spatial distribution of features, such as odor calls, can be isolated to specific time frames and compared to other data (environmental, engineering, demographic, etc.). Identifying odor impact trends early can help build a proactive approach to wastewater odor management and contribute to effective engagement with the community.

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