VAQUITA POPULATION TREND MONITORING SCHEME
BASED ON PASSIVE ACOUSTICS DATA

PROGRESS REPORT FOR

STEERING COMMITTEE

SECOND MEETING

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1. Introduction

This report presents partial results of an investigation aimed at estimating the population trend of the vaquita, through monitoring of individuals of the species with passive acoustic techniques, as designed by a group of experts (Rojas Bracho et al., 2010).

This monitoring scheme is based on the installation of autonomous acoustic detectors, named C-POD, at 48 sites within the Refuge for Protection of Vaquita and buoys used to delimitate it. Given illegal fishing activities that happen inside the refuge, the 48 sampling sites were restricted to the three months before the shrimping season (June to September) when fishing intensity is the lowest of the year. Efforts have been made to continue sampling all year-round with detectors deployed in the buoys. However, we have experienced loss rates that are not sustainable. This report describes the different alternatives of mooring methods essayed that have failed, as well as a recent attempt to solve this problem.

In its current development, the monitoring scheme envisages the attainment of six years of sampling, in order to detect small increases or decreases of the population during this period. This information is essential to adjust the actions taken by the Mexican government to recover the species. If population is not monitored directly, given its critical current level, it could reach very low numbers before the recovery program is adjusted in a timely manner.

This report presents data obtained during the first three years of sampling, and depicts the analysis done until now. It includes the identification of vaquita acoustic events and the implementation of a model to estimate the acoustic encounter rate trend in relationship with time, as an index of population trend.

2. Field activities

2.1. Acoustic detectors deployed on delimiting buoys of Protection Refuge

The only feasible way to gather acoustic data all year round, in order to understand distribution patterns of vaquita acoustic activity, is to deploy acoustic detectors in the buoys delimiting the Protection Refuge (Figure 1A). Until now three mooring methods have been essayed, all with poor results in terms of equipment recovery.

The first method (Figure 1B) consisted in a metallic frame attached to the buoy chain, which was the platform to moor the acoustic detector. Using this method 13 moorings were deployed on July (6) and September 2011 (remaining 7), in buoys 1, 2, 3, 5, 6, 7, 8, A, B, C, F, G and I (Figure 1A). Buoys 4, D and E were not in place previous to deployment. During December 2011 and January 2012 it was tried to retrieve the acoustic detectors. At first, according to plans, it was tried to grasp the line holding the detector (Figure 1B) with a hook inserted in the tip of a pole. This was successful only at Buoy 8. Further inspection using submersible camera and diving evidencing interaction with fishing or directed sabotage, finding no frames or frames detached of the chain, as well as entangled gillnet pieces (Figure 1C). Diving in the buoys resulted in the recovery of an additional detector in Buoy 2. Fishermen delivered later the acoustic detectors
deployed in buoys 1 and A. Hence, only one out of 13 detectors was recovered in the proper way.

After the failure of the method described above, it was essayed to mooring acoustic detectors directly to the buoy chain using a snap shackle (Figure 1D). This was made by SCUBA diving. During this activity it was possible to check the buoys for the situation of the moorings described above. During January 31st and February 1st, 2012, twelve detectors were deployed at buoys 1, 2, 3, 5, 6, 7, 8, A, B, F, G and I. Buoy C was not in place, in addition to ones at sites 4, D and E. On March 23rd, almost two months after deployment, it was possible to recover the detector at Buoy G, which was replaced by another with fresh batteries. On April 28th it was tried to recover detectors at buoys 2, 3, 5, 6, B and I, recovering only the one at Buoy 5, finding again evidences of fishing operations or directed theft. In fact the recovered detector was entangled in several folds of a net. Buoy F was removed for maintenance by PROFEPA, which delivered the detector deployed there to Biosphere Reserve. The one deployed at Buoy 8 was found by Biosphere Reserve personnel floating nearby. During May it was unsuccessfully tried to recover the reminder detectors at buoys 1, 7, A, B as well as the one redeployed in Buoy G during March. Summarizing, not accounting for Buoy F, it was possible to recover detectors only on two of the eleven buoys, although the detector redeployed at Buoy G was finally lost.

The mooring method depicted above was of difficult implementation, as it is needed diving to deploy and retrieve detectors. An alternative method is depicted in Figure 1E. A rope is attached to the weight holding the buoy and is hold extended with an anchor, where another rope is used to hold the acoustic detector. The rope is extended inside the Protection Refuge. The installation of the rope in the weights is not a job for amateurs, since it is a deep diving under extreme turbidity. As such, it was required the hiring of professional divers. To retrieve detectors a hook is towed behind a boat to grasp the rope and pull it to reach the detector. This method is thus similar to that used in the moorings that are deployed within the refuge (see next section). However, it will be not required to waste time searching for the rope with GPS positions, because the buoy marks the position clearly.

During September 7 to 9, 2012 (just previous to shrimp season), 11 moorings were placed on buoys 1, 2, 3, 5, 6, 7, 8, A, I, F and G (Figure 1A). The field operations team worked together with the divers. Once the diver went down and attached the rope to the buoy, a small boat was used to extended rope, into the Refuge, and threw the anchor along with the acoustic detector. The team stayed at the site for several minutes to ensure that all the rope gets submerged, without any sign on the surface.

Some days after the deployment PROFEPA removed buoys A and I for maintenance and bring back acoustic detectors, which gather, respectively, only 6 and 14 days of data. Efforts to recover the acoustic detectors were done first on November 22nd and five of the moorings were properly grasped and detectors retrieved (buoys 2, 5, 6, 8 and F). On December 14th one additional detector was retrieved at Buoy G and few days later a fisherman delivered the detector deployed at Buoy 7. Moorings at buoys 1 and 3 were not located after about two hours of searching effort. Hence, not accounting buoys A and
I, six out of the nine detectors deployed were properly located and retrieved, even in areas subjected to intense fishing operations.

**Figure 1.** A) Map showing the polygon of Vaquita Protection Refuge (solid line) and delimiting buoys (triangles). Broken line represents the seaward boundary of the Biosphere Reserve. B) First method to deploy acoustic detectors on buoys. C) How first method failed and way to mount detectors directly to buoy chain. D) Shackles used to mount CPOD to chain. E) Method to mooring detectors using a long rope attached to buoy weight.
After December 2012, detectors with fresh batteries were deployed at the buoys where moorings were found (2, 5, 6, 8, F and G). Unfortunately, by March 2013 none of the detectors were found. Hence, although after the first retrieving period the mooring method looked promising, it is evident that we still do not have a robust method to sample all year round in buoys.

As it is important for the monitoring scheme to gather data about distribution of the acoustic activity of vaquita all year round, and the deployment in buoys looks as the only feasible way to do it, a fourth mooring method was essayed on March 11th 2014. The same approach depicted above (Figure 1E) was used, but replacing all the materials with stainless steel, without any hand removable parts, supposing ropes were cut on the past trials. A couple of moorings were deployed in buoys G and I using SCUBA diving, holding the wire at about 15 meters below the surface. As the wire must tend to get buried into the bottom sediments, holding the wire not as close the bottom as in the past trials could help to properly grasp the wire during equipment retrieval. No acoustic detectors were placed in the mooring, waiting to review if moorings stay in place intact.

On April 12th the moorings were inspected. The one deployed at Buoy I was found after four attempts to grasp the wire, passing relatively close to the buoy. The one at Buoy G was not found after several passes at different distances from the buoy. It will be required to dive in the site to determine if it was stolen, moved by fishing operations or not effective anchoring, or because the wire got buried too deep in the sediments. The pieces of the mooring deployed at Buoy I look in good shape after one month of service, confirming the quality of the stainless steel used (Figure 2).

After reviewing by diving the mooring at Buoy G, as well as to review again the one at Buoy I, it will be decided the next steps. In case to find that moorings are there, other ones will be deployed at other buoys to continue with the trial, but no actual detectors will be used until determine that the design can assure the recovery of them.

Figure 2. Detail of river anchor, wires and lock used to construct the moorings to deploy acoustic detectors in the buoys delimiting the Protection Refuge for Vaquita. After one month of soaking it do not appears any trace of stain or damage.
2.2. Acoustic detectors deployed inside Protection Refuge

The moorings used to deploy acoustic detectors inside Protection Refuge are alike the ones used to deploy in Refuge buoys (Figure 1E). A main polypropylene rope, about 150 meters long connects two anchors with chain at every side. One of them is Danforth style and the other river kind. On the side of the river one a rope is connected which holds a small rigid buoy and acoustic detector (Figure 3). A piece of chain is placed in the middle point of the main rope to hold against the bottom, as the material has positive floatation and during trials the rope was visible in surface on some occasions.

The procedure to deploy the mooring and detector starts by launching the Danforth anchor at the sampling site. At the same time the geographical position is recorded in a handheld GPS. Then the boat is moved to the east in order to extend the line until it is determined that the anchor is resisting the pulling. At that time the river anchor is launched together with the holding line and detector. Again, position is recorded in GPS. The retrieval of the moorings is done by trawling a grasping hook behind the boat, using to navigate the GPS positions recorded at the time of deployment.

After three years of sampling the field operations team (three boats) has developed enough skills to efficiently do the job. On deployment every boat carries seven or eight moorings per trip, so the job can be completed in two days. On retrieval every boat recovers approximately five moorings per day. The technique is so refined that finding of the mooring main line takes in average 20 minutes since deployment of hook until grasping. Took the mooring on the boat takes another 20 minutes using human and boat power. Hence, it is considered that mooring method used inside Protection Refuge is working well and is not necessary to change anything.

In 2011, first year of formal sampling inside Refuge, moorings and detectors were deployed in the 48 sampling sites designed during 2009 Workshop (Rojas Bracho et al., 2010; Figure 4) between June 5 to 9. Operations to locate and retrieve then were carried out between September 9 and 25. During the first two weeks 38 of the 48 moorings deployed were located and retrieved, one of them without the acoustic detector (Figure 4). A couple of detectors were delivered to the staff of the Biosphere Reserve previous to the start of recovery tasks (sites 2 and 9; Figure 4), therefore there was no search effort at these sites. The CPOD deployed at site 45 was delivered during January 2012. The one deployed at site 3 was recovered during the retrieval of equipment deployed during 2013 sampling season. Six of the moorings were never found.

On early May 2012, we obtained information about the presence of dozens of fishing boats within the Refuge, sighted during a survey flight¹. Accordingly, it was decided to delay the deployment of detectors waiting for a reduction of fishing intensity. By June,

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we were reported that only a few boats had been found, so it was decided to install the detectors by the middle of this month.

![Diagram of moorings](image)

**Figure 3.** Sketch of the moorings used to deploy acoustic detectors inside Protection Refuge of Vaquita. The basic idea is to connect two anchors with a long rope that can later be grasped by means of a hook trawled behind a boat. No traces of the mooring are visible in surface in order to avoid theft. Location of anchors are marked in GPS that help later to know where to navigate to grasp the rope. A rope to hold the CPOS is attached to the side where river anchor is.

All 48 moorings of the monitoring scheme (Figure 4) were deployed between June 17 to 20. The field work to recover the moorings was carried out between September 17 and 22. A total of forty one moorings and detectors were recovered (Figure 3). One detector was delivered by a fisherman and the ones deployed at sites 11, 15 and 45 were recovered during the retrieval of equipment deployed during 2013 sampling season. As in 2011 sampling season, moorings at sites 17, 18 and 33 were not found.

It was decided not to deploy equipment at these sites during the 2013 sampling season, in order to avoid more equipment. Two of these sites are in the southwest boundary of the Vaquita Refuge and the other close to. Hence, frequent fishing operations could be the reason for the lost. After being informed of the reduction of fishing boats in the area, 34 moorings were deployed between June 15 and 16. Due to bad weather conditions the deployment of the reminder moorings took place on June 22 (7 moorings) and July 13 (4 moorings). The field work to recover the moorings was carried out between September 9 and 12. A total of 39 moorings and detectors were recovered (Figure 4). On
September 20 other detector was recovered. On October 1\textsuperscript{st}, a coordinated effort of three boats working side by side to cover more area, resulted in the additional retrieval of four detectors. Of the 45 moorings deployed only the one at site 3 was not located, which represents a loss of only 2.22\%. It is far the most successful sampling until now in regards to the loss of moorings in the field, not taking into account the three sites where no deployment occurred.

![Diagram of sampling sites inside Vaquita Protection Refuge](image)

**Figure 4.** Position of the sampling sites inside Vaquita Protection Refuge (upper map, numbered circles). Below are the results of moorings and acoustic detectors recovery on the three past sampling seasons. Sites not enclosed by any symbol are places where no moorings were found or sites where no moorings were deployed. Circles indicate places where data is available and squares sites where moorings were recovered without detector or detectors recovered without data.
3. CPOD performance

Inside the Protection Refuge for Vaquita have been deployed a total of 141 moorings and acoustic detectors. 128 of them have been recovered by means of the planned routine or delivered back by other persons. This represents a recovery rate of 90.78%.

CPODs store data in a 4GB SD card, into 4 files near 1GB the first three and a fourth smaller due to the presence of the settings file. The files are populated in order from 0 to 3 as data is gathered. Along the three years of sampling already completed only on 27 times had been necessary to use the fourth file (Table I). When this has happened, on 22 occasions (81%) this file has been damaged. In few occasions reformatting of the card with the dedicated program has resulted in few days of additional data. The fourth file has been necessary mainly on sampling sites at the northern portion of the Protection Refuge, where waters are shallower and noisier.

On other occasions the CPODs have recorded few days of data. As the equipment is deployed by three months at least, it is considered that gather less than 60 effective days is low. Gather less than 50 days is too low. In total less than 60 days of data have been gathered on 23 times, 10 of them at a very low level, including a case of gather only five days (Table I) noting that the angle never changed its turned off angle position. Only on six of these occasions have coincided with a damaged fourth file (Table I), all at a low level. All the very low days of data cases occurred during 2013. Again, these events tend to occur on shallow and noisy areas, except for the very low data cases that occurred in 2013. The cause of this must be investigated.

In total occurred 44 events of abnormal data gathering, which represents 34% of the total sampling inside Protection Refuge along the three years. A matter of concern is raised at noisy areas as well as the very low volumes of data gathered at some sites during 2013. It must be discussed during the second meeting of the Steering Committee.

4. Raw data analysis

Specialized CPOD program provided by the manufacturer of the equipment (Chelonia Limited) was used to identify Vaquita like click series. Every CP1 file is analyzed with KERNO classifier, which identifies series with narrow band high frequency (NBHF) clicks, potentially emitted by vaquitas, as well as wide band signals potentially emitted by other cetaceans like dolphins, sonars or other sources. This process creates CP3 files, which only contain information of the identified series, which greatly reduces the volume of data to be reviewed by the analysts.

Two analysts review all CP3 files to decide if the series identified as NBHF by KERNO classifier belong to vaquitas. A number of criteria are defined and recommended by the manufacturer, including click frequency and level, click duration (cycles), click band width, inter click interval and series envelope form. Analysts do not insert new series from inspection of data, but delete the ones not appearing as being emitted by vaquitas. At the end of the review use the export option to create text files containing 1 minute slices with ones if confirmed vaquita series were identified or zero if not. The minutes containing vaquita series are called Detection Positive Minutes (DPM).
Table I. Sites and PODs with events resulting in loss of data. The events are separated by year of sampling. D3 OK means that the fourth data file was written without error. D3 X means the fourth file had an error. Broken means that this POD was returned by a fisherman open and with the electronics board detached. Low means less than 60 days of data gathered but more than 50. For very low level actual number of day are shown. No angle change means that not a single click was stored as the angle of inclination of the POD never changed or the sensor was malfunctioning.

<table>
<thead>
<tr>
<th>Site</th>
<th>POD</th>
<th>Event</th>
<th>Days</th>
<th>POD</th>
<th>Event</th>
<th>Days</th>
<th>POD</th>
<th>Event</th>
<th>Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>998</td>
<td>Broken</td>
<td>Low</td>
<td>6</td>
<td>1341</td>
<td>D3 OK</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1336</td>
<td></td>
<td>21</td>
<td>12</td>
<td>1342</td>
<td>No angle change</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>1302</td>
<td></td>
<td>12</td>
<td>20</td>
<td>2041</td>
<td>31</td>
<td>21</td>
<td>1301</td>
<td>37</td>
</tr>
<tr>
<td>22</td>
<td>1347</td>
<td></td>
<td>Low</td>
<td>26</td>
<td>995</td>
<td>D3 OK</td>
<td>1506</td>
<td>D3 X</td>
<td>2048</td>
</tr>
<tr>
<td>27</td>
<td>1501</td>
<td>D3 X</td>
<td>Low</td>
<td>28</td>
<td>1009</td>
<td>D3 OK</td>
<td>1315</td>
<td>D3 X</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td></td>
<td></td>
<td></td>
<td>36</td>
<td>1350</td>
<td>D3 X</td>
<td>Low</td>
<td>1316</td>
<td>1332</td>
</tr>
<tr>
<td>37</td>
<td>1342</td>
<td></td>
<td>Low</td>
<td>38</td>
<td>1341</td>
<td>D3 X</td>
<td></td>
<td>1337</td>
<td>D3 X</td>
</tr>
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<td>39</td>
<td>992</td>
<td>D3 OK</td>
<td></td>
<td>39</td>
<td>1505</td>
<td>D3 X</td>
<td>Low</td>
<td>1331</td>
<td>D3 X</td>
</tr>
<tr>
<td>40</td>
<td>1348</td>
<td>D3 X</td>
<td></td>
<td>40</td>
<td></td>
<td></td>
<td>2047</td>
<td>D3 X</td>
<td></td>
</tr>
<tr>
<td>41</td>
<td>1349</td>
<td>D3 X</td>
<td></td>
<td>41</td>
<td></td>
<td></td>
<td>1320</td>
<td></td>
<td></td>
</tr>
<tr>
<td>42</td>
<td>1343</td>
<td>D3 X</td>
<td>Low</td>
<td>42</td>
<td>1333</td>
<td>D3 X</td>
<td>1349</td>
<td>D3 X</td>
<td></td>
</tr>
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<td>D3 X</td>
<td></td>
</tr>
<tr>
<td>45</td>
<td>1345</td>
<td></td>
<td>Low</td>
<td>45</td>
<td>1314</td>
<td>D3 X</td>
<td>1341</td>
<td>D3 OK</td>
<td></td>
</tr>
<tr>
<td>46</td>
<td>1346</td>
<td>D3 X</td>
<td>Low</td>
<td>46</td>
<td>1309</td>
<td>D3 X</td>
<td>1333</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td>48</td>
<td>1343</td>
<td>D3 X</td>
<td></td>
<td>48</td>
<td></td>
<td></td>
<td>1311</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

After the analysis of the first two sampling seasons data (2011-2012) it was noted that the “mechanics” of data displaying in CPOD program is complicated, needing to be changing displays with keystrokes constantly. To reduce this load on the analysts, and try to reduce time and facilitate analysis, a program was created using Visual Studio Express (Microsoft). This program uses the same CP1 and CP3 files to display data using a different “paradigm” (Figure 5). In one screen are presented all the acoustic parameters and click series are identified with color and number codes. Red dotes are displayed when parameter have NBHF like values. The routine to manage series is
improved and a text box presents information including the separation in time between series. Comments can be added which are sent to a csv file including a time tag. Log files are created in order to have complete control of the analysis process.

Figure 5. Display of the alternative program written to display CPOD data using a different “paradigm”. Top panel shows the contents of the CP3 file, identifying click series and their quality with numbers and colors. Second panel shows the contents of CP1 file. Next panels show, respectively, the click parameters frequency, duration, band width and the inter-click interval. Information area on the top shows controls, general information and the time to the previous series displayed. A box is available to capture comments in a log file.

5. Data 2011 - 2013

A program was written using Visual Studio Express to manage the csv files created by CPOD. This routine identifies the acoustic encounters according to the criterion explained above and creates csv files with the total number of DPMs and encounters per site and day, which is the sampling unit (site-day). After using the alternative analyzing program the CP3 files are read directly to create the csv files with the results.

After three sampling seasons a total of 127 sites have been analyzed, including 9,817 whole days and 6,270 acoustic encounters of vaquitas. An acoustic encounter is defined as all the identified clicks series separated consecutively by no more than 30 minutes. The next table shows data per year:

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sites</td>
<td>39</td>
<td>45</td>
<td>43</td>
<td>127</td>
</tr>
<tr>
<td>Days</td>
<td>3,019</td>
<td>3,785</td>
<td>3,013</td>
<td>9,817</td>
</tr>
<tr>
<td>Encounters</td>
<td>2,151</td>
<td>2,374</td>
<td>1,745</td>
<td>6,270</td>
</tr>
</tbody>
</table>
Figure 6 presents these data graphically. The horizontal axis is time and number of encounters per site per day in the vertical one. Every blue point represents the number of encounters in the station-day, in the date when this occurred. The cyan bars represent the distribution of encounter rate (encounters/site/day) per year. It is clear that the sampling units with zero encounters are extremely frequent.

![Figure 6. Scatter plot displaying all the data available for analysis. Blue points are individual site days at the date when they occurred. Cyan bars show the proportion of site-days with zero encounters, 1-2 encounters and 3 or more encounters, departing from a Poisson pattern.](image)

6. An approximation to model encounter rate trend

The ratio of the variance over average encounter rate for 2011, 2012 and 2013 data, respectively, is 4.15, 3.94 and 3.82, which clearly departs from a Poisson distribution. Data is then over dispersed or zero inflated as compared with this distribution. Taken this into account, the model approximation used here was made supposing encounter rate data is distributed according to a negative binomial distribution, parameterized as (Ver Hoef and Boveng, 2007; Lord and Park, 2008; Lindén and Mäntyniemi, 2011;):

\[
f(y; \lambda, r) = \frac{\Gamma(y+r)}{\Gamma(y+1)\Gamma(r)} \left( \frac{r}{\lambda+r} \right)^r \left( \frac{\lambda}{\lambda+r} \right)^y \quad \text{Equation 1}
\]

where \(y\) is the value for which calculate the negative binomial probability, \(\lambda\) is the average and \(r\) is the dispersion parameter.

The simplest function to model the relationship between encounter rate and time could be, given that the domain of the encounter rate is in the positive numbers is:

\[
y_t = e^{a+bt} \quad \text{Equation 2}
\]

where \(y_t\) is the encounter rate at time \(t\), and \(a\) and \(b\) are parameters to be estimated. Then, the parameter \(b\) determines the change of the encounter rate as the time progress. Negative values of this parameter mean a decreasing rate of the encounter rate, which is
an indication of a negative trend of the population, given that no distribution shifts or acoustic behavior changes occur in the same period.

However, this simple model supposes that no other factors affect the encounter rate as measured in the sampling process described in this report.

The acoustic encounter rate is not homogeneously distributed along the Protection Refuge (Figure 7). The northern portion shows the lowest acoustic activity of vaquitas, while the southwest portion has the highest encounter rates. It appears that vaquitas tend to echolocate more frequently around sites 14 and 32, as indicated by the average distribution of the three sampling seasons combined (Figure 7).

The simple model described in Equation 2 could overcome this issue by using a balanced sampling, including data only for days when all sampling stations have data. It occurs because acoustic detectors are not deployed all in the same day, and every one turns off on different days depending on battery duration and data volume gathered. This approach would result in discarding valuable data; hence a better approach is to use a model including the variability due to distribution of encounter rate. On the other hand, it is known that the Upper Gulf of California basin is characterized by a very extreme tidal range, which could result in differential encounter rates between neap and spring tides. A model including all these variables could be used to better understand the encounter rate trend with time:

\[
\bar{y} = e^{b_0 + (b_y y) + (b_{lat} lat) + (b_{lon} lon) + (b_t t)} \quad \text{Equation 3}
\]

Where \( \bar{y} \) is the average acoustic encounter rate given the variables in the model, \( y \) is the sampling year (considering the change of acoustic detection rate is negligible during the three months of sampling season), \( \text{lat} \) and \( \text{lon} \) are the latitude and longitude of the sampling sites, \( t \) is the tide expressed as the difference between the upper and lower tide level of the sampling day, \( b_0 \) is the intercept parameter of the model and \( b_y, b_{lat}, b_{lon}, b_t \) are the parameters (coefficients) determining the relationship between the variables in the model and the acoustic encounter rate.

The relationship between encounter rate with year and tide could be intuitively linear; however the spatial structure seen in Figure 7 is more complicated and could be better modeled with a polynomial. Hence it was essayed the fitting of second and third degree polynomials on latitude and longitude:

\[
\bar{y} = e^{b_0 + (b_y y) + (b_{lat} lat) + (b_{lat2} lat^2) + (b_{lat3 lat^3}) + (b_{lon} lon) + (b_{lon2} lon^2) + (b_{lon3} lon^3) + (b_t t)} \quad \text{Equation 4}
\]

Where \( b_{lat2} \) and \( b_{lon2} \) are the parameters added to the model with second degree polynomials for squared latitude and longitude. Parameters \( b_{lat3} \) and \( b_{lon3} \) are the case for third degree. The second degree model is the Equation 4 not including the cubic terms.

A Bayesian approach was used to estimate the parameters of the models (Gelman et al., 1995; Kruschke, 2011) using non-informative uniform priors for parameters centered at a value of zero. AD Model Builder (ADMB; Fournier et al., 2012) was used to estimate
posterior distributions using the Monte Carlo Markov Chain (MCMC) routine as implemented in ADMB using the Metropolis-Hastings algorithm (Chib and Greenberg, 1995). Likelihood portion of the joint posterior distribution was based on negative binomial distribution as in Equation 1, considering the dispersion parameter $r$ as a hyper-parameter to be estimated, using a semi-informative uniform prior bounded between 0.01 and 5.00.

Figure 7. Acoustic encounter rate contour maps based on data for every sampling year and all data combined. The map for all data shows the position of the sampling sites. It is evident the heterogeneous distribution of the encounter rate and the highest acoustic activity around sites 14 and 32.
The optimization phase of ADMB (maximum likelihood estimation) was used to verify that models were numerically stable and correctly specified. Then the MCMC was run using zero as starting values for parameters except for dispersion parameter $r$, which was started at a value of 0.2.

All models (equations 2, 3 and the polynomials in equation 4) were fitted using 500,000 MCMC simulations. Data for the simple model in Equation 2 only include days when all stations for the corresponding year have data, totaling 5,554 site-days.

Table below shows a description of the posterior distributions of parameter $b$ for simple model and $b_y$ for lineal and polynomial models. Figure 8 shows histograms of the same posteriors. For all models 95% credible intervals do not contain positive values for these parameters and the probability of a value lower than zero is greater than 0.99, indicating that a positive trend of encounter rate with time is unlikely.

<table>
<thead>
<tr>
<th>Model</th>
<th>Min</th>
<th>Max</th>
<th>Average</th>
<th>Median</th>
<th>Std dev</th>
<th>Equal Tail Interval</th>
<th>Highest Density Interval</th>
<th>Credibility value &lt;0</th>
</tr>
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<tbody>
<tr>
<td>Simple</td>
<td>-0.3834</td>
<td>0.0334</td>
<td>-0.1771</td>
<td>-0.1770</td>
<td>0.0484</td>
<td>-0.2723 -0.0825</td>
<td>-0.2706 -0.0810</td>
<td>0.9999</td>
</tr>
<tr>
<td>Lineal</td>
<td>-0.2147</td>
<td>0.0465</td>
<td>-0.0851</td>
<td>-0.0851</td>
<td>0.0308</td>
<td>-0.1455 -0.0246</td>
<td>-0.1449 -0.0242</td>
<td>0.9971</td>
</tr>
<tr>
<td>Second degree</td>
<td>-0.2206</td>
<td>0.0491</td>
<td>-0.0903</td>
<td>-0.0903</td>
<td>0.0313</td>
<td>-0.1521 -0.0289</td>
<td>-0.1521 -0.0290</td>
<td>0.9980</td>
</tr>
<tr>
<td>Third degree</td>
<td>-0.2440</td>
<td>0.0295</td>
<td>-0.0932</td>
<td>-0.0930</td>
<td>0.0310</td>
<td>-0.1540 -0.0322</td>
<td>-0.1542 -0.0325</td>
<td>0.9988</td>
</tr>
</tbody>
</table>

The simple model estimates that average encounter rate in the Protection Refuge changed from around 0.76 encounters/day/site in 2011 to 0.53 in 2013, approximately a 16% annual decreasing.

Fixing latitude and longitude at the position of site 14, and tide difference at 2 meters, lineal, second degree and third degree models estimate negative annual changes of the average encounter rate of around 8.16, 8.64 and 8.90% respectively.

It is known that vaquita population decreased at an approximate annual rate of 7.6% between 1997 and 2008 (Gerrodette et al., 2011). On the other hand, acoustic encounter rate decreased at an annual rate of approximately 8.34% (Jaramillo Legorreta, 2008), meaning that acoustic encounter rate could vary in direct proportion with abundance. Taking into account that since 2008 the Mexican Government initiated a program to reduce fishing effort that kills vaquitas, the adjustment of the simple model is unlikely as compared with the models including variation due to geographical position and tide in the sampling site.

Figure 9 shows output of the models as contours of encounter rate fixing the tide difference at 2 meters and year 2013. Comparing with data under these conditions, the third degree model appears to explain better the spatial variation of the encounter rate, although not locating precisely the sites with higher acoustic activity.

In conclusion, the modelling exercise after three sampling periods appear to have a high credibility that the acoustic encounter rate has been decreasing since 2011 at a rate higher than 8% per year, indicating the same fate for vaquita population level.
Figure 8. Posterior distributions of parameters $b$ (top histogram) and $b_y$ for the four models fitted. It is noted that simple model results in a more dispersed distribution. The other distributions are very alike, varying slightly in its mode.
Figure 9. Acoustic encounter rate contour maps based on output of the models with space variation. It is evident that third degree model is the one better representing the map based on data. The output of models is obtained fixing for year 2013 and tide range 2 meters.
7. Literature Cited


Executive Summary

Mid-project results of the vaquita acoustic monitoring project indicate a critical decline in vaquita numbers since 2011. Raw data indicate declines of 7.5% and 14.9% in average Detection Positive Minutes (an index of vaquita presence) from 2011 to 2012 and from 2012 to 2013, respectively (Figure 1). Preliminary analyses indicate that the decline in vaquita abundance is likely to be even greater. Small populations are vulnerable to cumulative, interacting risks, like inbreeding depression and increased variability in population growth rates, that can accelerate their decline to extinction. As the vaquita population declines, it may reach a point of no return from which recovery is not possible. We do not know what that point is for the vaquita. Based on concerns about inbreeding depression, Jaramillo et al. (2007) chose 50 adults, a number identified by Franklin (1980) necessary to retain reproductive fitness. Adults likely comprise about half of the current vaquita population, so the threshold of total abundance (all ages) would be about 100. During the 65a Scientific Committee meeting, CIRVA members produced an analysis, required by the Government of Mexico, which used a Bayesian model to estimate the 2013 abundance of the vaquita population. The posterior distribution for that year’s abundance indicated a best estimate of 189 individuals.

Figure 1. Average Detection Positive Minutes (DPM) per day with the percent decline between years.

The Steering Committee (Committee) found that deployment and retrieval of acoustic monitoring devices (C-PODs) inside the Vaquita Refuge had been very successful in the first 3 years of the 6-year project; the scientists conducting the study retrieved more than 90% of deployed C-PODs. The C-PODs performed well and collected data that would have been sufficient to detect the hoped-for 4%/year increase over a 5-year interval (6 survey
periods), had such an increase occurred. Two scientists processed the data independently and they compared their results with those of a computer program designed to detect porpoise vocalizations. The comparison produced nearly perfect agreement. The Committee agreed that the data were of high quality and that the performance of the entire team carrying out this project was exceptional.

The Committee examined summary statistics for the raw data and the results of detailed analyses to estimate the rate of change in vaquita abundance. All approaches indicate that vaquita population is declining and the rate of decline appears to be as great or greater than any decline ever recorded for the population. Given their critically low abundance, all plausible scenarios indicate that without effective remedial action the species could become extinct in the near future.

The Committee discussed factors that may confound interpretation of the data. Notably, the highest detection rates were from the southernmost C-PODs, which could indicate that vaquitas moved southward out of the monitoring area. However, past surveys have shown vaquita distribution to be remarkably consistent over a long time period (Figure 2). Those visual data indicate an area of longstanding low density next to the southwest boundary of the Refuge. Currently, monitoring data for the area are not available because all C-PODs placed there (on or just outside the Refuge’s southwest boundary) were lost. To confirm that vaquita are not using the area around the southwest boundary of the Refuge, the Committee recommended adding 5 C-PODs just inside that boundary. The Committee also recommended increasing enforcement along the boundary during the monitoring season and replacing C-PODs frequently during the season to ensure quick recovery of the collected data.

![Figure 2](image_url)

*Figure 2. Visual detections (red and green circles) from the two major ship surveys with the ship track lines shown as light gray lines. The C-POD locations are shown as black dots and the Vaquita Refuge is outlined in black.*
The Committee agreed that the estimated annual rates of decline from 2011 to 2013 are so severe and the vaquita's status so serious that immediate action is essential to save this species. Nonetheless, to confirm its findings, the Committee is planning an immediate review of its data, analyses, and preliminary findings. The Committee is seeking the necessary funds and has identified a small group of experts well suited to provide the review.
Full Report

The Committee of the acoustic monitoring program for vaquita held its second meeting on April 24-25 in Ensenada, Mexico. The objectives of the meeting were to review and evaluate the technical aspects of the passive acoustic monitoring project and to consider results midway through the project to determine if the monitoring program should be adjusted. The acoustic monitoring devices are called C-PODs. Technical aspects include –

- the mooring of C-PODs within, on the delimiting buoys, and outside the Vaquita Refuge (hereafter referred to as the refuge)
- the performance of the C-PODs, and
- the interpretation of the C-POD data.

The Committee also considered how to communicate results to authorities and other interested non-scientist parties including the communities near vaquita habitat.

C-POD Bottom Mooring

Deployment and retrieval of C-PODs within the refuge has been very successful with a retention rate of more 90% (Figure 3). Equipment retrieval takes on average 15-20 minutes. If retrieval was unsuccessful with a single panga, most C-PODs were retrieved when three pangas were used. Details of deployment and recovery are given in the Progress Report (Appendix 1). The Committee recommended that the methods developed by the Mexican crew to moor and retrieve C-PODs using light-weight, inexpensive materials should be published as a technical note so that others could benefit from their success.

C-POD Perimeter Buoy Mooring

The monitoring program was devised to collect year-round data from a set of perimeter buoys (which mark the boundaries of the Vaquita Refuge) to characterize potential seasonal or annual shifts in vaquita distribution. The expectation was that fishermen would avoid entangling their gear in the buoys, which would make them good mounts for the C-PODs if the C-PODs were not visible from the surface. The investigators used a series of buoy-C-POD configurations (details in Appendix 1). Unfortunately, nearly all C-PODs deployed with buoys were lost. Over the 3 years of the study perimeter buoys produced 971 C-POD-days of data. Had the perimeter buoys been successful there would have been approximately 13,000 C-POD-days of data. Whether the loss was intentional or accidental (i.e., by entanglement in fishing gear), it is clear that buoys cannot be used for attachment of C-PODs. The investigators are using dummy C-PODs to test new methods for anchoring C-PODs near or on the Refuge boundary.
Figure 3. Position of the sampling sites inside the Vaquita Refuge (upper map, numbered circles). Below are the results of moorings and acoustic detectors deployed in 2011, 2012, and 2013. C-PODs were not deployed at sites 17, 18, and 33 in 2013 (X’s). Circles indicate sites where data are available, diamonds indicate all equipment lost at that site, and squares indicate sites where the mooring was recovered without the detector or the detector was recovered without any data.

Loss of Moorings Used to Monitor Vaquita Outside Vaquita Refuge

The 2009 Acoustic Monitoring Workshop and CIRVA (2012) recommended study of vaquitas outside the Refuge. Barbara Taylor provided funding for a study to estimate the loss rate of acoustic stations for monitoring vaquitas outside the Refuge. The mooring design used outside the Refuge was the same as that used inside the Refuge.

Eight moorings with dummy C-PODS were deployed on 30 July 2013 outside the western edge of the Refuge (Figure 4). Recovery of C-PODS was attempted in September 2013 prior to shrimp season and the average recovery time was 50 minutes (range 18-61 minutes). Two (25%) of eight moorings were recovered, both from the area west of the Refuge. None of the C-PODs along the southwest refuge boundary were recovered. As noted above, this boundary is the area of greatest interest because C-PODs just inside this boundary have the highest vaquita detection rate, indicating that vaquita may move outside the Refuge in this area.
The high loss rate was not expected because the moorings were deployed during the period of lowest fishing effort. However, large commercial trawlers are used to catch fish during this period and in this area, and this part of the vaquita’s range has no protection from any type of fishing. The Committee discussed methods to reduce the loss rate through the use of 3 recovery pangas, short-term deployments, or even guarding the C-PODs. Given the high loss rate, these alternatives seemed unlikely to yield sufficient data without great expenditure from guarding the C-PODs or deploying large numbers of them to compensate for the loss rate.

**Monitoring the Refuge boundary and Outside Areas**

The Refuge boundary and outside areas are not monitored and such monitoring does not appear to be feasible in the foreseeable future. The Committee discussed several alternatives. One suggestion was to use the *Koipai* (a boat capable of deploying acoustic monitoring devices) to conduct stationary sampling year round. Again, the purpose of such sampling would be to determine if changes in vaquita detection rates within the Refuge are due to shifts in distribution.

For the purpose of distinguishing a population decline from a shift in population distribution, the more important question is whether the population moves outside the Refuge in the summer months when the C-PODs are deployed. Past visual surveys conducted in fall months indicate the distribution of vaquita in fall months is consistent, which argues against a shift in distribution. If, as suspected, the vaquita do not shift their distribution, then the most likely explanation for a reduced number of acoustic detections within the refuge is a reduced number of vaquitas.

The Committee decided that a sailboat-towed array would not provide sufficient data to test the hypothesis of a distribution shift even if the boat operated day and night. Instead, the Committee recommended hiring fishermen to do daily C-POD deployments in the area.
south of the Refuge. The first year would be used to determine the amount of data necessary to test the hypothesis of movement of vaquitas outside the Refuge as a reason for the observed decline within the Refuge. That information would be used to plan future monitoring in this area.

**C-POD Performance**

Overall performance of C-PODs was good. Several programming problems limited the amount of data that could be stored by some C-PODs. However, those limitations do not appear to have compromised the data collected and the programming problems will be remedied before the next season. Further details are given in Appendix 1.

**Preliminary Results**

Figure 5 illustrates the level of acoustic monitoring effort (i.e., days of acoustic monitoring per C-POD station) for different years.

![Figure 5. Number of days of monitoring effort for each sampling site indicated by circle size](image)

**Validation of Vaquita Signal Identification (GENENC)**

A blind test was conducted to assess potential detection differences between two independent data analysts (E. Nieto and G. Cardenas) and a computer algorithm developed to identify porpoise acoustic signals (GENENC). GENENC is an encounter classifier and can be used as a validation reference tool. It is designed to minimize errors in classifying other noises as vaquita clicks (false positives). GENENC uses information from an encounter, which is defined as a sequence of trains with no gap longer than 2 min. It does not detect all porpoise encounters that could be identified by a skilled analyst, but the loss is relatively small and program performance should be stable over time, making it an easy-to-use reference tool. The analysts reviewing the data visually followed the same guidelines as used in the computer algorithm. Their results and those of GENENC were nearly identical in terms of the numbers of detection positive minutes (DPM/day correlations: 2011: 0.974; 2012: 0.976; 2013: 0.974). Of the 1528 DPMs recorded, 1521 were considered to be true detections of vaquita and 7 (0.4%) were considered false positives caused by detection of dolphins. Details for these analyses and the GENENC and visual classification comparison are given in Appendix 2.
Although the Committee considered the difference between the analysts’ results and computer results to be negligible, it also suggested that the error rates of the two analysts should be compared and presented. Quantifying the error rate between the two analysts could be accomplished using Mark-Recapture methods with the same dataset.

Jaramillo developed an “all on one screen” display to facilitate data analysis. This program uses the same CP1 raw data and CP3 processed data files created by CPOD program, visually displays needed information, and reduces analysis time. The Committee commended Jaramillo for developing such a useful tool and recommended it be made available to others.

**Choice of Metrics: Clicks per Day (Clicks/day), Encounters per Day (Enc/day), or Detection Positive Minutes per Day (DPM/day)**

The Committee discussed which units of acoustic activity should be used in the analysis. ‘Encounters’ are periods of detected activity defined by some silent gap at each end. (These data have been analysed using a 30-minute gap). However, most acoustic researchers have moved away from counting encounters to either counting clicks or DPMs. Each metric has some advantages and some disadvantages.

Counts of clicks per day may conflate behaviour with presence, as animals click more rapidly during prey capture and more slowly while travelling. In the data collected to date the difference between mean click rates in successive years is low. (Mean click rates per second within identified click trains in 2011, 2012 and 2013 were 86.9, 90.8 and 92.8, respectively).

Click counts have the advantage that they will reflect group size reasonably if animals in a group generally continue clicking. This is because the sound beam produced by the animal is very narrow and is recorded only briefly as it sweeps across the hydrophone, and the recording only becomes saturated at very high animal densities.

The sum of train durations is the measure of duration of detectability that is most resistant to saturation. In this data set it correlates tightly with click counts (linear regression over 3 years $R^2 = 0.98$). It has not (yet) been widely used, but may be expected to avoid conflating behaviour with density, and to reflect group size.

DPM also is not much affected by behaviour but can saturate during periods of high local density. It is widely used and understood in acoustic monitoring of echo-locating cetaceans. In this data set DPM and click counts correlate closely (Figure 6).
Figure 6. Relationship between the yearly click count and the yearly total DPM).

The SAMBAH project is assessing the greatly depleted harbor porpoise population of the Baltic Sea. That project is using detection positive seconds, which is a more appropriate measure for estimating absolute abundance using a distance-detection function that is being developed for that project.

Porpoise positive days, PPD, has been used to present and communicate information collected with PODs in the German Baltic. This measure is easy to understand, but it saturates at densities well below those seen in this study at the sampling sites with the highest detection rates. It would measure the spread of the population rather than its size.

Encounters are the longest of the plausible measures and may be confounded because a long period is allowed between vocalizations. The total number of encounters also may not reflect group size and is affected strongly by animal movement speeds. For example, an increase might arise from the presence of dolphins or shifts in prey size or type (benthic to pelagic etc.) and this would tend to generate more, shorter, encounters from the same density of animals. If encounters are long, a reduction in logger sensitivity could increase encounter numbers by splitting them, a perverse effect, and encounter rates saturate locally if animal movement rates are low.

Visual surveys have shown that vaquita group size has remained constant over time, which indicates that the encounter-rate metric is less likely to be biased. Analysis of the acoustic monitoring data from 2011 to 2013 using encounters indicates that detection rates are declining in a manner that is broadly consistent with analytical results based on other measures. In this case, encounter rates also can be more easily compared to the findings of Jaramillo when he used different equipment and demonstrated the serious progressive decline in detection rates that – based on the 2011 to 2013 data – appears to be continuing. Assumptions are summarized in Table 1 with other considerations listed below.
Table 1. Assumptions required for use of different metrics to infer trends in vaquita numbers.

<table>
<thead>
<tr>
<th>Assumes:</th>
<th>Acoustic Units</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Encounters</td>
</tr>
<tr>
<td>Constant distribution of vaquitas over time</td>
<td>Y</td>
</tr>
<tr>
<td>Constant vaquita movement rates</td>
<td>Y</td>
</tr>
<tr>
<td>Constant click rates over time</td>
<td>N</td>
</tr>
<tr>
<td>Constant group size</td>
<td>Y</td>
</tr>
</tbody>
</table>

Other considerations:

In addition, the metric “encounters per day” –
- will saturate in high densities
- can be affected by noise (but less sensitive to saturation within a minute)
- is sensitive to definition of “encounter.”
- cannot include time-of-day covariates in models.

Both DPM and clicks/unit time are affected by noise saturation (>4096 samples/minute). Finally, the DPM metric is robust to movement rate and click rate changes.

Vaquita behavior is not well understood and we do not know how it changes from year to year. Therefore, the Committee recommended that the analysts test the sensitivity of the analytical results to the metric used. The aim of the sensitivity analysis would be to compare results and, if they agree, then conclusions are robust to the metric. If results differ, further research will be needed.

Effects of Dolphins on Vaquita Detections

Dolphins may cause vaquitas to decrease vocalizations, move away, or both (Eiren Jacobsen pers. comm.). As part of his Ph.D. research, Gustavo Cardenas is using the C-POD data to investigate the potential influence of dolphins on vaquita vocalization. The Committee welcomed this research and looks forward to seeing the results. His methods were as follows:
- He used a panga to conduct six surveys in the Refuge between August 2013 and March 2014.
- His most common cetacean sightings were long-beaked common dolphins, followed by Bryde’s whales, bottlenose dolphins, vaquitas, and humpback whales.
- During encounters with dolphins, he navigated the panga toward their swimming trajectory and deployed a buoy with acoustic detectors to record their vocalizations.
- During the surveys he also recorded noise produced by fishing boats and shrimp trawlers. He also recorded those boats with his panga engine turned off to provide more accurate recordings. In one location, he observed long-beaked common
dolphins feeding behind trawlers and bottlenose dolphin feeding on fishery discards. To get a better recording, he deployed a buoy with a recorder and then moved the panga 500 m from the buoy.

- He will analyze his acoustic recordings using the C-POD software.
- When he has characterized the vocalizations of the different species and the sound signatures of the recorded vessels, he will then use the data to determine whether the presence of dolphins or vessels affect the acoustic detection of vaquitas.

**Effects of Noise on Detectability of Vaquitas**

Very few vaquita were detected in the northwestern portion of the Refuge. The C-PODs in this area were saturated by noise from moving sediments and snapping shrimps. Jaramillo tested whether vaquita click trains might have been missed in this area because of noise masking by inserting a vaquita signal into a file from a noisy sampling location. GENERC was able to find that signal more than 80% of the time. These results gave the Committee confidence that vaquita densities are actually low in these high-noise areas.

**Trends in Vaquita Abundance Inferred from Acoustic Detections**

The acoustic monitoring project assumes that acoustic detections are proportional to the number of vaquitas: more vaquitas will make more detectable sounds. If acoustic monitoring effort were equal across the vaquita’s range and the vaquitas did not change their behavior in some significant manner, then the raw number of detected vaquita sounds should change at the same rate as vaquita abundance. However, if the monitoring effort changes in different years, the interpretation of the data becomes more complex. The dataset examined here has just such complexities because C-PODs that were not recovered in 2011 were from locations with high detection levels in 2012 and 2013. Also, the amount of data from each C-POD is not equal (Figure 5). In this preliminary analysis, the raw results are given first followed by the results of several analytical models that account for differing effort across the Refuge and over time.

**Spatial Results**

Figure 7 shows smoothed levels of acoustic detections of vaquitas within the Refuge and for the different years. Blank areas in the 2011 map indicate areas where no acoustic data were collected (see effort data in Figure 5). The Committee noted that the areas of missing data in 2011 corresponded to areas of high acoustic detections in 2012 and 2013 (sample sites 10, 16, 32 and 34). Like the earlier visual data, these acoustic data also indicate that areas where vaquitas are detected remain relatively constant through time.
Figure 7. Acoustic encounter rate contour maps based on data for every sampling year and all data combined. Raw encounter rate data are smoothed by Kriging. The map for all data (i.e., all three years) shows the position of the sampling sites. The results illustrate the heterogeneous distribution of the encounter rate and the areas of highest acoustic activity around sites 14 and 32.

Trends Using Raw Data

Based on three sampling seasons the investigators have analyzed a total of 127 site-years; a site-year describes the data collected at one site over a one-year period. The data cover 9,817 complete site-days and include 6,270 acoustic encounters with one or more vaquitas.
An acoustic encounter is defined as any series of identified clicks separated by no silent intervals longer than 30 minutes. Table 2 shows the raw data for all metrics considered.

**Table 2. Total effort and different measures of acoustic detection including DPM and encounters.**

<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sites per year</td>
<td>39</td>
<td>45</td>
<td>43</td>
<td>127</td>
</tr>
<tr>
<td>Site-days</td>
<td>3,019</td>
<td>3,785</td>
<td>3,013</td>
<td>9,817</td>
</tr>
<tr>
<td>DPMs</td>
<td>8,665</td>
<td>9,766</td>
<td>6,897</td>
<td>25,328</td>
</tr>
<tr>
<td>Encounters</td>
<td>2,151</td>
<td>2,374</td>
<td>1,745</td>
<td>6,270</td>
</tr>
<tr>
<td>Average DPM/site/day</td>
<td>2.91</td>
<td>2.69</td>
<td>2.29</td>
<td>2.64</td>
</tr>
<tr>
<td>Average encounters/site/day</td>
<td>0.71</td>
<td>0.63</td>
<td>0.58</td>
<td>0.64</td>
</tr>
</tbody>
</table>

The raw annual percent change is given in Table 3 for each of the metrics discussed. As can be seen in Figure 3 the decline from 2011 to 2012 estimated from the raw data will underestimate the actual decline because 2011 was missing some of the C-PODs expected to have high numbers of vaquita detections.

**Table 3. Estimated percent change in annual vaquita abundance using encounters/day and DPM/day and based on the raw data. All the measures indicate strong declines in vaquita detections and, therefore, abundance (Figure 1 presents the same information graphically).**

<table>
<thead>
<tr>
<th></th>
<th>2011 to 2012</th>
<th>2012 to 2013</th>
<th>2011 to 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Encounters/day</td>
<td>-11.3%</td>
<td>-7.9%</td>
<td>-18.3%</td>
</tr>
<tr>
<td>DPM/day</td>
<td>-7.5%</td>
<td>-14.9%</td>
<td>-21.3%</td>
</tr>
</tbody>
</table>

Figure 1 shows the DPM metric in Table 3 as a bar chart. All indicate strong declines in vaquita detections.

**Stochastic Model of Acoustic Activity**

The measures of vaquita acoustic activity (encounters/day or DPM/day) are essentially count data. The encounter rate data are over-dispersed relative to a Poisson distribution: approximately 75% of the data were zero, and the ratio of variance to mean was about 4 to 1 (Appendix 1). An analysis by Jaramillo indicates that the negative binomial distribution fits the encounter rate data adequately (Figure 8). Additional research should be undertaken to investigate whether this distribution also would fit the DPM data.
Figure 8. Histograms of data (encounters/day for 2012, red bars) compared to model-predicted rates (posterior probabilities multiplied by total encounters, blue bars). The plot on the right has a discontinuous y-axis to show more detail for the non-zero data. $\lambda$ is the mean and $r$ is the dispersion parameter of the negative binomial distribution.

Models to Adjust for Uneven Spatial Effort

Several analytical models were used to adjust the raw data for uneven spatial effort in different years. Jaramillo examined three alternative approaches to address this spatial-temporal inconsistency. First, he used data only from those days and sites where monitoring effort occurred each year. That approach was less than optimal because it greatly reduces the amount of data. Second, he used a Bayesian polynomial model of encounter rate (see details in Appendix 1 and summary of results in Table 4), and third, he created another analytical model that treated each station as a categorical variable (see details in Appendix 3). The last of those approaches estimated a 19.9% decline per year.
Table 4. Results from Bayesian modeling (needs adjusting to show different results for encounter rate and DPM for 3rd degree only...needs explanation)

<table>
<thead>
<tr>
<th>Model</th>
<th>Min</th>
<th>Max</th>
<th>Average</th>
<th>Median</th>
<th>Std dev</th>
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<th>Highest Density Interval</th>
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<td>Simple (Encounters)</td>
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<td>-0.1771</td>
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<td>-0.2723 -0.0825</td>
<td>-0.2706 -0.0810</td>
<td>0.9999</td>
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<tr>
<td>Linear (Encounters)</td>
<td>-0.2147</td>
<td>0.0465</td>
<td>-0.0851</td>
<td>-0.0851</td>
<td>0.0308</td>
<td>-0.1455 -0.0246</td>
<td>-0.1449 -0.0242</td>
<td>0.9971</td>
</tr>
<tr>
<td>Second order (Encounters)</td>
<td>-0.2206</td>
<td>0.0491</td>
<td>-0.0903</td>
<td>-0.0903</td>
<td>0.0313</td>
<td>-0.1521 -0.0289</td>
<td>-0.1521 -0.0290</td>
<td>0.9980</td>
</tr>
<tr>
<td>Third order (Encounters)</td>
<td>-0.2440</td>
<td>0.0295</td>
<td>-0.0932</td>
<td>-0.0930</td>
<td>0.0310</td>
<td>-0.1540 -0.0322</td>
<td>-0.1542 -0.0325</td>
<td>0.9988</td>
</tr>
<tr>
<td>Third order (DPM)</td>
<td>-0.2642</td>
<td>0.0178</td>
<td>-0.1263</td>
<td>-0.1263</td>
<td>0.0346</td>
<td>-0.1944 -0.0577</td>
<td>-0.1956 -0.0593</td>
<td>0.9998</td>
</tr>
</tbody>
</table>

The Committee noted that the one-dimensional polynomial models used to describe geographic differences in relative abundance did not completely capture the geographic patterns in the contour maps of the raw data (Appendix 1, Figure 7). Barlow suggested using Generalized Additive Models (GAMs) with two-dimensional splines to correct that shortcoming. Jaramillo provided Barlow with the data he used in his Bayesian analyses, and Barlow completed the GAMs overnight. Barlow modeled both acoustic encounters per day (as defined by Jaramillo, see Appendix 1) and DPM (also summarized on a daily basis) and created models for year alone (without geographic components), for year plus a 2-dimensional smooth plate spline, and for year plus site (C-POD station number) as a categorical variable. He used Simon Wood’s R package (mgcv) for all model fits assuming a negative binomial distribution for the acoustic indices of vaquita abundance (R code is available Appendix 4).

The GAMs analyses (Table 5) confirmed the declines that were seen in Jaramillo’s Bayesian models, but indicated rates of population decline that were generally higher than presented in Table 4 and Appendix 1. Models with just time (year) and with time & tide showed decreases of 10-12% per year. When geographic differences in vaquita abundance were added to models (either as a 2-D spline fit of latitude/longitude or as a categorical factor for C-POD station number), the results indicated rates of decline of 20-26% per year. The 20% decline per year is similar to the Bayesian model of encounter rate based on categorical station numbers. For direct comparison to Jaramillo’s Bayesian polynomial model, Barlow fit a GAMs model using 3rd-degree polynomials of latitude and longitude (separately) and linear effects of time and tide. The results indicated slightly higher rates of decline (~10% per year) than the median values of the Baysian model but much lower rates of decline than were seen with 2-dimensional spline fits.
The GAMs with 2-dimensional spline fits to latitude & longitude explained the geographic patterns in the acoustic data better than the polynomial model, as indicated by the higher percentages of explained deviances (Table 1). The geographic model of relative vaquita abundance (Figures 9 and 10) also better captured the patterns of geographic distribution seen in the smoothed contour plots (Appendix 1, Fig. 7).

Table 5. Estimated decline in vaquita abundance based on GAMs analyses of encounters per day and DPM per day. Results include the exponential annual rate of population change (r) and its standard error and the percent explained deviance for each model.

<table>
<thead>
<tr>
<th>Model</th>
<th>Encounter rate</th>
<th>DPM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>se-r</td>
</tr>
<tr>
<td>Year</td>
<td>0.109</td>
<td>0.021</td>
</tr>
<tr>
<td>Year + tide</td>
<td>0.108</td>
<td>0.029</td>
</tr>
<tr>
<td>Year + 2D-spline(Lat*Long)</td>
<td>0.234</td>
<td>0.027</td>
</tr>
<tr>
<td>Year + categorical station</td>
<td>0.219</td>
<td>0.028</td>
</tr>
<tr>
<td>Year + poly(Lat,3) + poly(Long,3) + Tide</td>
<td>0.104</td>
<td>0.024</td>
</tr>
</tbody>
</table>

Figure 9. Relative abundance of vaquitas based on a GAMs analysis using a 2-dimensional smooth plate spline fit to DPMs per sample day from 2011-2013 C-POD monitoring stations. The smoothed values are truncated at the edge of the achieved grid of sampling stations.
The Committee asked whether the spatial model would show changes in the rate of decline between the two time periods (2011-2012 and 2012-2013). To address that question, Barlow used GAMs models with a spline fit for year and a 2-dimensional spline fit for latitude & longitude. The results (Figure 11) indicated that the rate of decline was higher during the first time period than during the second for both measures of acoustic density (encounters and DPMs per day).
Table 6 summarizes the results of these different models for encounter rate (the metric with complete results for the Bayesian analyses). For the model types that were run using both the Bayesian and likelihood approaches (GAMs), the rates of decline were similar. The estimated rate of decline from the polynomial model differs substantially from the results of the other models, indicating that the polynomial model may not adequately reflect the spatial complexity of the data.

Table 6. Rates of decline ($r$) and precision for different models and different statistical approaches.

<table>
<thead>
<tr>
<th>Model</th>
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<th>Generalized Additive Model</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$r$</td>
<td>$r$</td>
</tr>
<tr>
<td>Simple</td>
<td>-0.171</td>
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<tr>
<td>Categorical</td>
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<tr>
<td>2-D spline</td>
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</tr>
<tr>
<td>Polynomial</td>
<td>-0.093</td>
<td>-0.099</td>
</tr>
</tbody>
</table>

Refining our Understanding of the Trend Models

All the above-described analytical results indicate that vaquita abundance is declining rapidly. A decline on the order of 8-10% annually would be sufficient to call for strong and swift management action. A decline on the order of 20% would warrant an even stronger response including drastic measures to halt the decline and prevent imminent extinction.
Because the results presented here have potentially grave implications for conservation efforts, the Committee is calling for their immediate review. Specifically, the Committee recommends the following steps be taken immediately.

1) The investigators write descriptions of the models summarized in this report with sufficient detail to allow replication by independent analysts,
2) They put the data in files for analysis using the 3 different metrics discussed,
3) The Committee selects an expert panel of at least 3 statisticians and modelers,
4) The investigators send the data and model descriptions to the expert panel so they have at least 2 weeks with the materials,
5) The Committee convenes the expert panel to work together (preferably in person but potentially remotely) with the appropriate members of the Committee to write a report with the objective of providing an estimate of the current rate of decline.

The following modelers were suggested as appropriate for this important task: Len Thomas, Justin Cooke, Jeff Moore, Andre Punt, Russell Leaper, Jay Ver Hoef and Jeff Laake. These modelers would work with Armando Jaramillo and Jay Barlow from the Committee. The Committee believes this work must be completed by June 30.

**Recommendations for the 2014 Acoustic Monitoring Season**

The Committee was very satisfied with the deployment and retrieval of C-PODs within the Refuge. However, it also believes that vaquita distribution near the southern border warrants more study. The visual data (Figure 1 and Figure 12) show a low density right next to the southwest boundary in an area not currently monitored with C-PODs. Because maintaining C-PODs on the boundary buoys has been unsuccessful and experimental C-PODs put just outside the Refuge were all lost, the Committee recommends adding 5 C-PODs in the southern area inside the Refuge where visual detections were low to ensure that the vaquita movement outside the Refuge has not contributed to their apparent decline. The Committee also recommends increasing enforcement along this boundary during the monitoring season and replacing C-PODs frequently during the season to obtain as much data as quickly as possible. In addition, the Committee recommends deploying the PROFEPA mother ship to the southernmost tip of the Refuge during the monitoring season and requesting deployment of a C-POD from the ship. Finally, the Committee recommends forwarding to CIRVA and the Presidential Commission on Vaquita the idea of paying fishermen to deploy C-PODs for daily periods just south of the Refuge. The data collected would help construct better boundaries for the Refuge and improve confidence that trends estimated from the acoustic monitoring project are representative for vaquitas.

**Summary of Committee Recommendations**

- Increase enforcement including along the southern boundary during the monitoring season
- Adding 5 C-PODs in the southern area just inside the refuge
- Paying fishermen to deploy C-PODs for daily periods just south of the refuge during monitoring season
- Publishing a technical note on the successful methods developed to moor and retrieve C-PODs using light-weight, inexpensive materials
- Making new visual display developed by Jaramillo for C-POD to facilitate C-POD analysis publicly available
• Test sensitivity of analytical results to the type of metric rates used (encounters, detection positive minutes, clicks)
• Immediately advancing analysis of results using independent analysts in an expert panel

Figure 12. The locations of the 5 new C-PODs should be within the gray box shown inside the Refuge along the southwest boundary. The C-PODs should be placed as close to the boundary as is safe from fishery entanglement, which would include areas of low visual detections (in the middle of the southwestern boundary) and high visual detections (towards the southern tip of the Refuge).

Acknowledgements
The workshop was funded by US Marine Mammal Commission. The research was funded between 2010 and 2013 by Mexico Minister of Environment, Instituto Nacional de Ecologia, The Ocean Foundation, Fonds de Dotation pour la Biodiversité, Cousteau Society, WWF México, WWF US, The Mohamed bin Zayed Species Conservation Fund and Barb Taylor.
Appendix 1

VAQUITA POPULATION TREND MONITORING PROGRAM
BASED ON PASSIVE ACOUSTICS DATA

PROGRESS REPORT FOR
STEERING COMMITTEE
SECOND MEETING

Ensenada, B.C., México
April 24-25, 2014

1. Introduction

This report presents partial results of an investigation aimed at estimating the population trend of the vaquita, through monitoring of individuals of the species with passive acoustic techniques, as designed by a group of experts (Rojas Bracho et al., 2010).

This monitoring program is based on the installation of autonomous acoustic detectors, named C-POD, at 48 sites within the Refuge for Protection of Vaquita and buoys used to delimitate it. Given illegal fishing activities that happen inside the refuge, the 48 sampling sites were restricted to the three months before the shrimping season (June to September) when fishing intensity is the lowest of the year. Efforts have been made to continue sampling all year-round with detectors deployed in the buoys. However, we have experienced loss rates that are not sustainable. This report describes the different alternatives of mooring methods essayed that have failed, as well as a recent attempt to solve this problem.

In its current development, the monitoring program envisages the attainment of six years of sampling, in order to detect small increases or decreases of the population during this period. This information is essential to adjust the actions taken by the Mexican government to recover the species. If population is not monitored directly, given its critical current level, it could reach very low numbers before the recovery program is adjusted in a timely manner.

This report presents data obtained during the first three years of sampling, and depicts the analysis done until now. It includes the identification of vaquita acoustic events and the implementation of a model to estimate the acoustic encounter rate trend in relationship with time, as an index of population trend.
2. Field activities

2.1. Acoustic detectors deployed on delimiting buoys of Protection Refuge

The only feasible way to gather acoustic data all year round, in order to understand distribution patterns of vaquita acoustic activity, is to deploy acoustic detectors in the buoys delimiting the Protection Refuge (Figure 1A). Until now three mooring methods have been essayed, all with poor results in terms of equipment recovery.

The first method (Figure 1B) consisted in a metallic frame attached to the buoy chain, which was the platform to moor the acoustic detector. Using this method 13 moorings were deployed on July (6) and September 2011 (remaining 7), in buoys 1, 2, 3, 5, 6, 7, 8, A, B, C, F, G and I (Figure 1A). Buoys 4, D and E were not in place previous to deployment. During December 2011 and January 2012 it was tried to retrieve the acoustic detectors. At first, according to plans, it was tried to grasp the line holding the detector (Figure 1B) with a hook inserted in the tip of a pole. This was successful only at Buoy 8. Further inspection using submersible camera and diving evidencing interaction with fishing or directed sabotage, finding no frames or frames detached of the chain, as well as entangled gillnet pieces (Figure 1C). Diving in the buoys resulted in the recovery of an additional detector in Buoy 2. Fishermen delivered later the acoustic detectors deployed in buoys 1 and A. Hence, only one out of 13 detectors was recovered in the proper way.

After the failure of the method described above, it was essayed to mooring acoustic detectors directly to the buoy chain using a snap shackle (Figure 1D). This was made by SCUBA diving. During this activity it was possible to check the buoys for the situation of the moorings described above. During January 31st and February 1st, 2012, twelve detectors were deployed at buoys 1, 2, 3, 5, 6, 7, 8, A, B, F, G and I. Buoy C was not in place, in addition to ones at sites 4, D and E. On March 23rd, almost two months after deployment, it was possible to recover the detector at Buoy G, which was replaced by another with fresh batteries. On April 28th it was tried to recover detectors at buoys 2, 3, 5, 6, B and I, recovering only the one at Buoy 5, finding again evidences of fishing operations or directed theft. In fact the recovered detector was entangled in several folds of a net. Buoy F was removed for maintenance by PROFEPA, which delivered the detector deployed there to Biosphere Reserve. The one deployed at Buoy 8 was found by Biosphere Reserve personnel floating nearby. During May it was unsuccessfully tried to recover the reminder detectors at buoys 1, 7, A, B as well as the one redeployed in Buoy G during March. Summarizing, not accounting for Buoy F, it was possible to recover detectors only on two of the eleven buoys, although the detector redeployed at Buoy G was finally lost.

The mooring method depicted above was of difficult implementation, as it is needed diving to deploy and retrieve detectors. An alternative method is depicted in Figure 1E. A rope is attached to the weight holding the buoy and is hold extended with an anchor, where another rope is used to hold the acoustic detector. The rope is extended inside the
Protection Refuge. The installation of the rope in the weights is not a job for amateurs, since it is a deep diving under extreme turbidity. As such, it was required the hiring of professional divers. To retrieve detectors a hook is towed behind a boat to grasp the rope and pull it to reach the detector. This method is thus similar to that used in the moorings that are deployed within the refuge (see next section). However, it will be not required to waste time searching for the rope with GPS positions, because the buoy marks the position clearly.

During September 7 to 9, 2012 (just previous to shrimp season), 11 moorings were placed on buoys 1, 2, 3, 5, 6, 7, 8, A, I, F and G (Figure 1A). The field operations team worked together with the divers. Once the diver went down and attached the rope to the buoy, a small boat was used to extended rope, into the Refuge, and threw the anchor along with the acoustic detector. The team stayed at the site for several minutes to ensure that all the rope gets submerged, without any sign on the surface.

Some days after the deployment PROFEPA removed buoys A and I for maintenance and bring back acoustic detectors, which gather, respectively, only 6 and 14 days of data. Efforts to recover the acoustic detectors were done first on November 22\textsuperscript{nd} and five of the moorings were properly grasped and detectors retrieved (buoys 2, 5, 6, 8 and F). On December 14\textsuperscript{th} one additional detector was retrieved at Buoy G and few days later a fisherman delivered the detector deployed at Buoy 7. Moorings at buoys 1 and 3 were not located after about two hours of searching effort. Hence, not accounting buoys A and I, six out of the nine detectors deployed were properly located and retrieved, even in areas subjected to intense fishing operations.

After December 2012, detectors with fresh batteries were deployed at the buoys where moorings were found (2, 5, 6, 8, F and G). Unfortunately, by March 2013 none of the detectors were found. Hence, although after the first retrieving period the mooring method looked promising, it is evident that we still do not have a robust method to sample all year round in buoys.

As it is important for the monitoring program to gather data about distribution of the acoustic activity of vaquita all year round, and the deployment in buoys looks as the only feasible way to do it, a fourth mooring method was essayed on March 11\textsuperscript{th} 2014. The same approach depicted above (Figure 1E) was used, but replacing all the materials with stainless steel, without any hand removable parts, supposing ropes were cut on the past trials. A couple of moorings were deployed in buoys G and I using SCUBA diving, holding the wire at about 15 meters below the surface. As the wire must tend to get buried into the bottom sediments, holding the wire not as close the bottom as in the past trials could help to properly grasp the wire during equipment retrieval. No acoustic detectors were placed in the mooring, waiting to review if moorings stay in place intact.
Figure 1.  A) Map showing the polygon of Vaquita Protection Refuge (solid line) and delimiting buoys (triangles). Broken line represents the seaward boundary of the Biosphere Reserve. B) First method to deploy acoustic detectors on buoys. C) How first method failed and way to mount detectors directly to buoy chain. D) Shackles used to mount CPOD to chain. E) Method to mooring detectors using a long rope attached to buoy weight.
On April 12th the moorings were inspected. The one deployed at Buoy I was found after four attempts to grasp the wire, passing relatively close to the buoy. The one at Buoy G was not found after several passes at different distances from the buoy. It will be required to dive in the site to determine if it was stolen, moved by fishing operations or not effective anchoring, or because the wire got buried too deep in the sediments. The pieces of the mooring deployed at Buoy I look in good shape after one month of service, confirming the quality of the stainless steel used (Figure 2).

After reviewing by diving the mooring at Buoy G, as well as to review again the one at Buoy I, it will be decided the next steps. In case to find that moorings are there, other ones will be deployed at other buoys to continue with the trial, but no actual detectors will be used until determine that the design can assure the recovery of them.

![Figure 2. Detail of river anchor, wires and lock used to construct the moorings to deploy acoustic detectors in the buoys delimiting the Protection Refuge for Vaquita. After one month of soaking it do not appears any trace of stain or damage.](image)

### 2.2. Acoustic detectors deployed inside Protection Refuge

The moorings used to deploy acoustic detectors inside Protection Refuge are alike the ones used to deploy in Refuge buoys (Figure 1E). A main polypropylene rope, about 150 meters long connects two anchors with chain at every side. One of them is Danforth style and the other river kind. On the side of the river one a rope is connected which holds a small rigid buoy and acoustic detector (Figure 3). A piece of chain is placed in the middle point of the main rope to hold against the bottom, as the material has positive floatation and during trials the rope was visible in surface on some occasions.

The procedure to deploy the mooring and detector starts by launching the Danforth anchor at the sampling site. At the same time the geographical position is recorded in a handheld GPS. Then the boat is moved to the east in order to extend the line until it is determined that the anchor is resisting the pulling. At that time the river anchor is
launched together with the holding line and detector. Again, position is recorded in GPS. The retrieval of the moorings is done by trawling a grasping hook behind the boat, using to navigate the GPS positions recorded at the time of deployment.

After three years of sampling the field operations team (three boats) has developed enough skills to efficiently do the job. On deployment every boat carries seven or eight moorings per trip, so the job can be completed in two days. On retrieval every boat recovers approximately five moorings per day. The technique is so refined that finding of the mooring main line takes in average 20 minutes since deployment of hook until grasping. Took the mooring on the boat takes another 20 minutes using human and boat power. Hence, it is considered that mooring method used inside Protection Refuge is working well and is not necessary to change anything.

In 2011, first year of formal sampling inside Refuge, moorings and detectors were deployed in the 48 sampling sites designed during 2009 Workshop (Rojas Bracho et al., 2010; Figure 4) between June 5 to 9. Operations to locate and retrieve them were carried out between September 9 and 25. During the first two weeks 38 of the 48 moorings deployed were located and retrieved, one of them without the acoustic detector (Figure 4). A couple of detectors were delivered to the staff of the Biosphere Reserve previous to the start of recovery tasks (sites 2 and 9; Figure 4), therefore there was no search effort at these sites. The CPOD deployed at site 45 was delivered during January 2012. The one deployed at site 3 was recovered during the retrieval of equipment deployed during 2013 sampling season. Six of the moorings were never found.

On early May 2012, we obtained information about the presence of dozens of fishing boats within the Refuge, sighted during a survey flight\(^1\). Accordingly, it was decided to delay the deployment of detectors waiting for a reduction of fishing intensity. By June, we were reported that only a few boats had been found, so it was decided to install the detectors by the middle of this month.

All 48 moorings of the monitoring program (Figure 4) were deployed between June 17 to 20. The field work to recover the moorings was carried out between September 17 and 22. A total of forty one moorings and detectors were recovered (Figure 3). One detector was delivered by a fisherman and the ones deployed at sites 11, 15 and 45 were recovered during the retrieval of equipment deployed during 2013 sampling season. As in 2011 sampling season, moorings at sites 17, 18 and 33 were not found.

Figure 3. Sketch of the moorings used to deploy acoustic detectors inside Protection Refuge of Vaquita. The basic idea is to connect two anchors with a long rope that can later be grasped by means of a hook trawled behind a boat. No traces of the mooring are visible in surface in order to avoid theft. Location of anchors are marked in GPS that help later to know where to navigate to grasp the rope. A rope to hold the CPOS is attached to the side where river anchor is.

It was decided not to deploy equipment at these sites during the 2013 sampling season, in order to avoid more equipment. Two of these sites are in the southwest boundary of the Vaquita Refuge and the other close to. Hence, frequent fishing operations could be the reason for the lost. After being informed of the reduction of fishing boats in the area, 34 moorings were deployed between June 15 and 16. Due to bad weather conditions the deployment of the reminder moorings took place on June 22 (7 moorings) and July 13 (4 moorings). The field work to recover the moorings was carried out between September 9 and 12. A total of 39 moorings and detectors were recovered (Figure 4). On September 20 other detector was recovered. On October 1st, a coordinated effort of three boats working side by side to cover more area, resulted in the additional retrieval of four detectors. Of the 45 moorings deployed only the one at site 3 was not located, which represents a loss of only 2.22%. It is far the most successful sampling until now in regards to the loss of moorings in the field, not taking into account the three sites where no deployment occurred.
Figure 4. Position of the sampling sites inside Vaquita Protection Refuge (upper map, numbered circles). Below are the results of moorings and acoustic detectors recovery on the three past sampling seasons. Sites not enclosed by any symbol are places where no moorings were found or sites where no moorings were deployed. Circles indicate places where data is available and squares sites where moorings were recovered without detector or detectors recovered without data.

3. CPOD performance

Inside the Protection Refuge for Vaquita have been deployed a total of 141 moorings and acoustic detectors. 128 of them have been recovered by means of the planned routine or delivered back by other persons. This represents a recovery rate of 90.78%.

CPODs store data in a 4GB SD card, into 4 files near 1GB the first three and a fourth smaller due to the presence of the settings file. The files are populated in order from 0 to 3 as data is gathered. Along the three years of sampling already completed only on 27 times had been necessary to use the fourth file (Table I). When this has happened, on 22
occasions (81%) this file has been damaged. In few occasions reformatting of the card with the dedicated program has resulted in few days of additional data. The fourth file has been necessary mainly on sampling sites at the northern portion of the Protection Refuge, where waters are shallower and noisier.

On other occasions the CPODs have recorded few days of data. As the equipment is deployed by three months at least, it is considered that gather less than 60 effective days is low. Gather less than 50 days is too low. In total less than 60 days of data have been gathered on 23 times, 10 of them at a very low level, including a case of gather only five days (Table I) noting that the angle never changed its turned off angle position. Only on six of these occasions have coincided with a damaged fourth file (Table I), all at a low level. All the very low days of data cases occurred during 2013. Again, these events tend to occur on shallow and noisy areas, except for the very low data cases that occurred in 2013. The cause of this must be investigated.

In total occurred 44 events of abnormal data gathering, which represents 34% of the total sampling inside Protection Refuge along the three years. A matter of concern is raised at noisy areas as well as the very low volumes of data gathered at some sites during 2013. It must be discussed during the second meeting of the Steering Committee.

4. Row data analysis

Specialized CPOD program provided by the manufacturer of the equipment (Chelonia Limited) was used to identify Vaquita like click series. Every CP1 file is analyzed with KERNO classifier, which identifies series with narrow band high frequency (NBHF) clicks, potentially emitted by vaquitas, as well as wide band signals potentially emitted by other cetaceans like dolphins, sonars or other sources. This process creates CP3 files, which only contain information of the identified series, which greatly reduces the volume of data to be reviewed by the analysts.

Two analysts review all CP3 files to decide if the series identified as NBHF by KERNO classifier belong to vaquitas. A number of criteria are defined and recommended by the manufacturer, including click frequency and level, click duration (cycles), click band width, inter click interval and series envelope form. Analysts do not insert new series from inspection of data, but delete the ones not appearing as being emitted by vaquitas. At the end of the review use the export option to create text files containing 1 minute slices with ones if confirmed vaquita series were identified or zero if not. The minutes containing vaquita series are called Detection Positive Minutes (DPM).
Table I. Sites and PODs with events resulting in loss of data. The events are separated by year of sampling. D3 OK means that the fourth data file was written without error. D3 X means the fourth file had an error. Broken means that this POD was returned by a fisherman open and with the electronics board detached. Low means less than 60 days of data gathered but more than 50. For very low level actual number of day are shown. No angle change means that not a single click was stored as the angle of inclination of the POD never changed or the sensor was malfunctioning.

<table>
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<th>Event</th>
<th>Days</th>
<th>POD</th>
<th>Event</th>
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<td></td>
<td></td>
<td>1349</td>
<td>D3 X</td>
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<td>Low</td>
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<td>D3 X</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>37</td>
<td>1342</td>
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<td>47</td>
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<td>992</td>
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<td></td>
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<td>D3 X</td>
</tr>
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<td>1348</td>
<td>D3 X</td>
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<td>D3 X</td>
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<td>D3 X</td>
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<td></td>
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<td>34</td>
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<td>1343</td>
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<td>Low</td>
<td>1333</td>
<td>D3 X</td>
<td></td>
<td></td>
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<td>D3 X</td>
</tr>
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<td>44</td>
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<td>2040</td>
<td>D3 X</td>
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<tr>
<td>45</td>
<td>1345</td>
<td>Low</td>
<td></td>
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<td>D3 X</td>
<td></td>
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<td>1341</td>
<td>D3 OK</td>
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<td>46</td>
<td>1346</td>
<td>D3 X</td>
<td>Low</td>
<td>1309</td>
<td>D3 X</td>
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<td></td>
<td>1333</td>
<td>Low</td>
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<td>D3 X</td>
<td></td>
<td></td>
<td>1311</td>
<td>Low</td>
</tr>
</tbody>
</table>

After the analysis of the first two sampling seasons data (2011-2012) it was noted that the “mechanics” of data displaying in CPOD program is complicated, needing to be changing displays with keystrokes constantly. To reduce this load on the analysts, and try to reduce time and facilitate analysis, a program was created using Visual Studio Express (Microsoft). This program uses the same CP1 and CP3 files to display data using a different “paradigm” (Figure 5). In one screen are presented all the acoustic parameters and click series are identified with color and number codes. Red dotes are
displayed when parameter have NBHF like values. The routine to manage series is improved and a text box presents information including the separation in time between series. Comments can be added which are sent to a csv file including a time tag. Log files are created in order to have complete control of the analysis process.

5. Data 2011 - 2013

A program was written using Visual Studio Express to manage the csv files created by CPOD. This routine identifies the acoustic encounters according to the criterion explained above and creates csv files with the total number of DPMs and encounters per site and day, which is the sampling unit (site-day). After using the alternative analyzing program the CP3 files are read directly to create the csv files with the results.

After three sampling seasons a total of 127 sites have been analyzed, including 9,817 whole days and 6,270 acoustic encounters of vaquitas. An acoustic encounter is defined as all the identified clicks series separated consecutively by no more than 30 minutes. The next table shows data per year:
<table>
<thead>
<tr>
<th></th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sites</td>
<td>39</td>
<td>45</td>
<td>43</td>
<td>127</td>
</tr>
<tr>
<td>Days</td>
<td>3,019</td>
<td>3,785</td>
<td>3,013</td>
<td>9,817</td>
</tr>
<tr>
<td>Encounters</td>
<td>2,151</td>
<td>2,374</td>
<td>1,745</td>
<td>6,270</td>
</tr>
</tbody>
</table>

Figure 6 presents these data graphically. The horizontal axis is time and number of encounters per site per day in the vertical one. Every blue point represents the number of encounters in the station-day, in the date when this occurred. The cyan bars represent the distribution of encounter rate (encounters/site/day) per year. It is clear that the sampling units with zero encounters are extremely frequent.

Figure 6. Scatter plot displaying all the data available for analysis. Blue points are individual site days at the date when they occurred. Cyan bars show the proportion of site-days with zero encounters, 1-2 encounters and 3 or more encounters, departing from a Poisson pattern.

6. An approximation to model encounter rate trend

The ratio of the variance over average encounter rate for 2011, 2012 and 2013 data, respectively, is 4.15, 3.94 and 3.82, which clearly departs from a Poisson distribution. Data is then over dispersed or zero inflated as compared with this distribution. Taken into account, the model approximation used here was made supposing encounter rate data is distributed according to a negative binomial distribution, parameterized as (Ver Hoef and Boveng, 2007; Lord and Park, 2008; Lindén and Määttäniemi, 2011;):

\[
f(y; \lambda, r) = \frac{\Gamma(y+r)}{\Gamma(y+1)\Gamma(r)} \left( \frac{r}{\lambda+r} \right)^r \left( \frac{\lambda}{\lambda+r} \right)^y \quad \cdots \cdots \quad \text{Equation 1}
\]

where \( y \) is the value for which calculate the negative binomial probability, \( \lambda \) is the average and \( r \) is the dispersion parameter.
The simplest function to model the relationship between encounter rate and time could be, given that the domain of the encounter rate is in the positive numbers is:

\[ y_t = e^{a+bt} \] .......................................................... Equation 2

where \( y_t \) is the encounter rate at time \( t \), and \( a \) and \( b \) are parameters to be estimated. Then, the parameter \( b \) determines the change of the encounter rate as the time progress. Negative values of this parameter mean a decreasing rate of the encounter rate, which is an indication of a negative trend of the population, given that no distribution shifts or acoustic behavior changes occur in the same period.

However, this simple model supposes that no other factors affect the encounter rate as measured in the sampling process described in this report.

The acoustic encounter rate is not homogeneously distributed along the Protection Refuge (Figure 7). The northern portion shows the lowest acoustic activity of vaquitas, while the southwest portion has the highest encounter rates. It appears that vaquitas tend to echolocate more frequently around sites 14 and 32, as indicated by the average distribution of the three sampling seasons combined (Figure 7).

The simple model described in Equation 2 could overcome this issue by using a balanced sampling, including data only for days when all sampling stations have data. It occurs because acoustic detectors are not deployed all in the same day, and every one turns off on different days depending on battery duration and data volume gathered. This approach would result in discarding valuable data; hence a better approach is to use a model including the variability due to distribution of encounter rate. On the other hand, it is known that the Upper Gulf of California basin is characterized by a very extreme tidal range, which could result in differential encounter rates between neap and spring tides. A model including all these variables could be used to better understand the encounter rate trend with time:

\[ \bar{y} = e^{b_0 + (b_y y) + (b_{lat} lat) + (b_{lon} lon) + (b_t t)} \] .................... Equation 3

Where \( \bar{y} \) is the average acoustic encounter rate given the variables in the model, \( y \) is the sampling year (considering the change of acoustic detection rate is negligible during the three months of sampling season), \( lat \) and \( lon \) are the latitude and longitude of the sampling sites, \( t \) is the tide expressed as the difference between the upper and lower tide level of the sampling day, \( b_0 \) is the intercept parameter of the model and \( b_y, b_{lat}, b_{lon}, b_t \) are the parameters (coefficients) determining the relationship between the variables in the model and the acoustic encounter rate.

The relationship between encounter rate with year and tide could be intuitively linear; however the spatial structure seen in Figure 7 is more complicated and could be better
modeled with a polynomial. Hence it was essayed the fitting of second and third degree polynomials on latitude and longitude:

\[ \bar{y} = e^{b_0 + (b_{y}y) + (b_{lat}lat) + (b_{lat}^2lat^2) + (b_{lon}lon) + (b_{lon}^2lon^2) + (b_{t}t)} \]  \hspace{1cm} \text{Equation 4}

Where \( b_{lat2} \) and \( b_{lon2} \) are the parameters added to the model with second degree polynomials for squared latitude and longitude. Parameters \( b_{lat3} \) and \( b_{lon3} \) are the case for third degree. The second degree model is the Equation 4 not including the cubic terms.

A Bayesian approach was used to estimate the parameters of the models (Gelman et al., 1995; Kruschke, 2011) using non-informative uniform priors for parameters centered at a value of zero. AD Model Builder (ADMB; Fournier et al., 2012) was used to estimate posterior distributions using the Monte Carlo Markov Chain (MCMC) routine as implemented in ADMB using the Metropolis-Hastings algorithm (Chib and Greenberg, 1995). Likelihood portion of the joint posterior distribution was based on negative binomial distribution as in Equation 1, considering the dispersion parameter \( r \) as and hyper-parameter to be estimated, using a semi-informative uniform prior bounded between 0.01 and 5.00.
Figure 7. Acoustic encounter rate contour maps based on data for every sampling year and all data combined. The map for all data shows the position of the sampling sites. It is evident the heterogeneous distribution of the encounter rate and the highest acoustic activity around sites 14 and 32.

The optimization phase of ADMB (maximum likelihood estimation) was used to verify that models were numerically stable and correctly specified. Then the MCMC was run using zero as starting values for parameters except for dispersion parameter $r$, which was started at a value of 0.2.

All models (equations 2, 3 and the polynomials in equation 4) were fitted using 500,000 MCMC simulations. Data for the simple model in Equation 2 only include days when all stations for the corresponding year have data, totaling 5,554 site-days.
Table below shows a description of the posterior distributions of parameter $b$ for simple model and $b_y$ for lineal and polynomial models. Figure 8 shows histograms of the same posteriors. For all models 95% credible intervals do not contain positive values for these parameters and the probability of a value lower than zero is greater than 0.99, indicating that a positive trend of encounter rate with time is unlikely.

<table>
<thead>
<tr>
<th>Model</th>
<th>Min</th>
<th>Max</th>
<th>Average</th>
<th>Median</th>
<th>Std dev</th>
<th>Equal Tail Interval</th>
<th>Highest Density Interval</th>
<th>Credibility value &lt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple</td>
<td>-0.3834</td>
<td>0.0334</td>
<td>-0.1771</td>
<td>-0.1770</td>
<td>0.0484</td>
<td>-0.2723</td>
<td>-0.0825</td>
<td>0.9999</td>
</tr>
<tr>
<td>Lineal</td>
<td>-0.2147</td>
<td>0.0465</td>
<td>-0.0851</td>
<td>-0.0851</td>
<td>0.0308</td>
<td>-0.1455</td>
<td>-0.0246</td>
<td>0.9971</td>
</tr>
<tr>
<td>Second degree</td>
<td>-0.2206</td>
<td>0.0491</td>
<td>-0.0903</td>
<td>-0.0903</td>
<td>0.0313</td>
<td>-0.1521</td>
<td>-0.0289</td>
<td>0.9980</td>
</tr>
<tr>
<td>Third degree</td>
<td>-0.2440</td>
<td>0.0295</td>
<td>-0.0932</td>
<td>-0.0930</td>
<td>0.0310</td>
<td>-0.1540</td>
<td>-0.0322</td>
<td>0.9988</td>
</tr>
</tbody>
</table>

The simple model estimates that average encounter rate in the Protection Refuge changed from around 0.76 encounters/day/site in 2011 to 0.53 in 2013, approximately a 16% annual decreasing.

Fixing latitude and longitude at the position of site 14, and tide difference at 2 meters, lineal, second degree and third degree models estimate negative annual changes of the average encounter rate of around 8.16, 8.64 and 8.90% respectively.

It is known that vaquita population decreased at an approximate annual rate of 7.6% between 1997 and 2008 (Gerrodette et al., 2011). On the other hand, acoustic encounter rate decreased at an annual rate of approximately 8.34% (Jaramillo Legorreta, 2008), meaning that acoustic encounter rate could vary in direct proportion with abundance. Taking into account that since 2008 the Mexican Government initiated a program to reduce fishing effort that kills vaquitas, the adjustment of the simple model is unlikely as compared with the models including variation due to geographical position and tide in the sampling site.

Figure 9 shows output of the models as contours of encounter rate fixing the tide difference at 2 meters and year 2013. Comparing with data under these conditions, the third degree model appears to explain better the spatial variation of the encounter rate, although not locating precisely the sites with higher acoustic activity.

In conclusion, the modelling exercise after three sampling periods appear to have a high credibility that the acoustic encounter rate has been decreasing since 2011 at a rate higher than 8% per year, indicating the same fate for vaquita population level.
Figure 8. Posterior distributions of parameters $b$ (top histogram) and $b_y$ for the four models fitted. It is noted that simple model results in a more dispersed distribution. The other distributions are very alike, varying slightly in its mode.
Figure 9. Acoustic encounter rate contour maps based on output of the models with space variation. It is evident that third degree model is the one better representing the map based on data. The output of models is obtained fixing for year 2013 and tide range 2 meters.
7. Literature Cited


Appendix 2. Assessment of false Vaquita detections in the output of GENENC, a generalised encounter classifier.

A visual inspection of acoustic data from the Vaquita monitoring program was carried out to test the accuracy of the Generalised Encounter Classifier (GENENC) and determine the rate at which false ‘detection positive minutes’, DPM, are likely to have been detected in error. GENENC is a classifier embodied in the CPOD.exe software. It can be applied to the data from all C-PODs.

**Method**

The data were examined in the UK by two analysts without any knowledge of the results obtained by the Mexican research term that had collected and also analysed the same data.

The CPOD.exe software was used to process the Vaquita files using the GENENC classifier, and filtered for narrow band high frequency, ‘NBHF’, click trains. The term ‘trains’ is synonymous with ‘series’ used in the report from the Mexican researchers.

All CP3 files that had one or more Vaquita DPMs were visually inspected and each false positive NBHF train marked by right clicking on the train and selecting “Mark train”.

The GENENC software uses the presence of other trains that occurred in the recent past or near future as a factor for classifying a click train. Therefore false detections are more likely to occur within close proximity of true positives, because of this element of ‘positive feedback’. Removing any single false train may not remove the minute from the DPM count as there may be other true NBHF trains within the same minute.

GENENC takes the output of the KERNO classifier that finds the trains and designates them as likely to be NBHF or not. GENENC assesses groups of likely NBHF trains that have no gap of more than 2 minutes. These GENENC encounters are not themselves used as a detection measure and are different from the encounters defined by the Mexican research term – those encounters have a 30 minute qualifying gap for the start of a new encounter.

The aim was to remove DPMs that did not have *any* true NBHF trains. The visual criteria used to assess the detected trains were based on the guidance in the cetacean validation guidelines (Validating cetacean detections.pdf). The main criteria were as follows:

To be accepted as a Vaquita encounter an encounter:

# must show these features in the identified trains or train fragments seen within 2 minutes:

1. 95% or more of the clicks must have frequencies in the range 120-150kHz.
2. Some ICIs greater than 10ms.
3. Some click durations above 10cycles.
4. Most loud clicks (>100) are >10 cycles.
# must not show these features:

1. Have a nearly constant ICI recurring through most of a minute or longer, due to clicks at Vaquita frequencies. This is the flat line seen on ICI displays of CP1 files, and it is due to SONARS.

2. An isolated train or pair of trains, (= where there are no 'good' train fragments, within 3 minutes, that fit (2-4) above ) must be excluded if:
   a. It consists of only 1 or 2 weak trains (SPL < 30).
   b. There are only weak trains (SPL < 50) with little shape to the SPL envelope or a ragged SPL profile. These could be 'WUTS' – weak unknown train sources.
   c. There are only fast trains (> 150/s = ICI < 7ms).
   d. If the trains are fast (ICI less than 5ms) and have <8 clicks.
   e. If the trains appear to be within multipath clusters. These could be chink spikes.
   f. Must not be a single train or sequence of trains with a very smooth rise in ICI (typically from 5ms or less) + little multipath + durations mostly below 10 cycles. These could be WUTS.
   g. Must not consist of loud short duration clicks as loud Vaquita clicks will be long.

3. No low frequencies (below 100kHz) that are either clustered with the multipath clusters of the detection (dolphins), or clustered with the train (mini-bursts). Low frequencies that occur at random are not a worry.

4. Trains close to dolphin encounters that show more than 20kHz range in their multipath clusters or do not show long weak clicks (the 'jump up, jump down' behaviour in the CPOD.exe graphical display).

Once all files had been assessed and false trains marked the NBHF DPMs were exported again and combined with the original list to see how many DPMs had been removed.

19.6 years of data consisting of 274 CPOD CP3 files were included, and were the whole data set available to us at the time.

**Results**

Of the 274 CP3 files 26 had Vaquita detections, so that trains in a total of 4.9 years of data were visually assessed.

59 files had dolphin detections, a total of 7.6 years of data. All files that had Vaquita detections also had dolphin detections.

The table below shows the results for those files that had Vaquita detections from GENENC, ordered by Vaquita DPM count, with red highlighting for files in which false DPMs were identified.
<table>
<thead>
<tr>
<th>File name</th>
<th>Vaquita detection positive minutes</th>
<th>Dolphin detection positive minutes</th>
<th>No of false Vaquita trains</th>
<th>Vaquita detection positive minutes after false trains removed</th>
<th>Vaquita detection positive minutes removed</th>
<th>Days On</th>
</tr>
</thead>
<tbody>
<tr>
<td>G5 CPOD Sitio 14 2011 06 05 POD1308 file01.CP3</td>
<td>1647</td>
<td>511</td>
<td>73</td>
<td>1631</td>
<td>16</td>
<td>72.04</td>
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<tr>
<td>F6 CPOD Sitio 19 2011 06 05 POD1319 file01.CP3</td>
<td>1102</td>
<td>208</td>
<td>14</td>
<td>1101</td>
<td>1</td>
<td>94.3</td>
</tr>
<tr>
<td>D6 CPOD Sitio 35 2011 06 08 POD1502 file01.CP3</td>
<td>1015</td>
<td>194</td>
<td>13</td>
<td>1013</td>
<td>2</td>
<td>86.7</td>
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<td>292</td>
<td>13</td>
<td>901</td>
<td>1</td>
<td>96.94</td>
</tr>
<tr>
<td>G7 CPOD Sitio 16 2010 06 05 POD1313 file01.CP3</td>
<td>848</td>
<td>294</td>
<td>15</td>
<td>846</td>
<td>2</td>
<td>81.75</td>
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<tr>
<td>C6 CPOD Sitio 43 2011 06 09 POD1506 file01.CP3</td>
<td>582</td>
<td>260</td>
<td>7</td>
<td>580</td>
<td>2</td>
<td>96.05</td>
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<tr>
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<td>296</td>
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<td>414</td>
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<tr>
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<td>254</td>
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<tr>
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<td>71.51</td>
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<tr>
<td>F4 CPOD Sitio 21 2011 06 06 POD1331 file01.CP3</td>
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<td>261</td>
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<td>114</td>
<td>0</td>
<td>69.8</td>
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<tr>
<td>E2 CPOD Sitio 27 2011 06 01 POD1006 file01.CP3</td>
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<td>500</td>
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<td>102.77</td>
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<tr>
<td>H7 CPOD Sitio 2 2011 06 07 POD998 file01.CP3</td>
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<td>602</td>
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<td>0</td>
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<tr>
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<td>162</td>
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<td>56</td>
<td>1</td>
<td>64.38</td>
</tr>
<tr>
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<td>639</td>
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<td>50</td>
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<td>64</td>
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<td>0</td>
<td>95.38</td>
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<tr>
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<td>166</td>
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<td>52.58</td>
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<tr>
<td>G4 CPOD Sitio 13 2011 06 06</td>
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<td>POD1337 file02.CP3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C4 CPOD Sitio 41 2011 06 09</td>
<td>2</td>
<td>7</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>23.39</td>
</tr>
<tr>
<td>POD1349 file01.CP3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I4 CPOD Sitio 1 2011 06 05</td>
<td>1</td>
<td>2668</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>81.63</td>
</tr>
<tr>
<td>POD1316 file01.CP3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E3 CPOD Sitio 28 2011 06 01</td>
<td>1</td>
<td>16</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>28.12</td>
</tr>
<tr>
<td>POD1009 file01.CP3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E4 CPOD Sitio 29 2011 06 02</td>
<td>1</td>
<td>13</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>9.68</td>
</tr>
<tr>
<td>POD1336 file02.CP3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td>7594</td>
<td>12354</td>
<td>171</td>
<td>7560</td>
<td>34</td>
<td>1814.54</td>
</tr>
</tbody>
</table>

The higher incidence of false DPMs in files with many true DPMs is an expected consequence of using a classifier with positive feedback. The relationship is shown in the graph below:

![Graph showing the relationship between false positive Vaquita detections and total number of Vaquita detections before false trains were removed.](image)

False positive Vaquita detections plotted against total number of Vaquita detections before false trains were removed.
Dolphin presence may contribute to false positive Vaquita DPM, especially in the case of Common Dolphins, *Delphinus delphis*, that produce clicks in a frequency range that overlaps that of the Vaquita. Dolphin encounters are distinguished by the presence of shorter clicks of greater bandwidth occurring across a wider frequency range. In the Upper Gulf dolphin detections are more frequent than Vaquita detections, even in the highest density areas for Vaquita.

In the data examined the relationship between false Vaquita detections identified as from dolphins and the prevalence of dolphins is shown in the scatter graph below:

![Scatter graph showing relationship between False Vq DPM and Dolphin DPM](image)

**Detection and error rates:**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>True Vaquita DPM per year</strong></td>
<td><strong>1521</strong></td>
</tr>
<tr>
<td><strong>False Vaquita DPM per year</strong></td>
<td><strong>7</strong></td>
</tr>
<tr>
<td>False Vaquita DPM as %True Vaquita DPM</td>
<td><strong>0.4%</strong></td>
</tr>
<tr>
<td>False Vaquita DPM as %Dolphin DPM</td>
<td><strong>0.3%</strong></td>
</tr>
</tbody>
</table>
**Discussion**

Table 2 shows that around 0.4% of detection positive minutes are false in this dataset.

None of the low Vaquita DPM count files contain false positives, indicating that Vaquita detections generate the very low level of false positives as a result of the positive feedback element in GENENC. This is a benign source of false positives as it does little other than increase the reported Vaquita detection rate by a very small fraction -approximately 0.4% and can safely be ignored as it will not affect trends or distributions. False positives from other sources could affect both trends and distribution, but are at a very low level.

Other issues:

**False negatives** were not looked for in the (raw) CP1 data. It is possible to do this by filtering the raw data to show only clicks with a SPL >30, kHz 125-150, duration > 15cycles in minutes with more than 8 such clicks. This does pick up some Vaquita detections that are not otherwise found. However, it would not improve the detection of a trend in the population unless the overall number of detections was very low, and would require further validation.

**WUTS** - weak unknown train sources. Such train sources have been seen in earlier T-POD data, and in C-POD data from the Upper Gulf. There appear to be few WUTS in this dataset but as their origin is unknown, and is thought to be biological, there is a possibility of large changes in incidence. WUTS indicate that some visual oversight of the data should be maintained, as the performance of GENENC where WUTS are prevalent is not well known.

**Dolphins** - false negatives - GENENC can only classify one species per encounter. So a high prevalence of dolphins would obscure some Vaquita detections. This circumstance is easily identified as dolphin detections can be obtained from the C-POD data. In the 2011-2013 data there is no increase in dolphins.

**Noise levels** will inevitably have some impact on the detectability of Vaquita and are also likely to affect their distribution. If noise levels showed progressive change this would require specific assessment as it is not demonstrated by GENENC. The raw C-POD data does provide information on noise levels.

**Conclusion**

Visual inspection and assessment shows that false positive Vaquita DPM is 0.4% of total Vaquita DPM for this dataset.

Most of the trains that have been found to be false positive Vaquita detections were detected by the GENENC algorithm due to their proximity to true positives within the same encounter and removing them would not alter the trend in detection positive minutes.

GENENC should be a stable reference tool to detect drift or bias in the performance of visual analysts but does not remove the need for visual oversight of the data and detections.
Appendix 3. **Model using categorical variables instead of geographical positions to account for spatial structure of encounter rate**

In this model latitude and longitude were replaced by a set of dummy variables constructed from the sampling sites. Only sites with at least 60 sampling days per year, and at least two years of data, were included in the data set. Hence, sites 3, 8, 12, 17, 18, 33 and 34 are not in the set, which results in a set of 41 dummy variables.

Every dummy variable takes a value of 1 when data corresponds to that site and the reminder dummy variables take a value of zero. In addition the model includes the year and tide information as in the models explained before:

\[
\hat{y} = e^{b_0 + (b_y y) + (b_t t) + (b_s1 s1) + \ldots + (b_s48 s48)}
\]

Where \(b_{sn}\) are the coefficients for every sampling site \(sn\), being \(n\) the sampling site number as in Figure 3.

The model was fitted using also ADMB. Its optimization routine was used to estimate point values and standard deviations of the coefficients of the model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Point</th>
<th>s.d.</th>
<th>Parameter</th>
<th>Point</th>
<th>s.d.</th>
<th>Parameter</th>
<th>Point</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(b_0)</td>
<td>-2.850</td>
<td>9003.000</td>
<td>(b_{s4})</td>
<td>3.455</td>
<td>9003.000</td>
<td>(b_{s23})</td>
<td>1.262</td>
<td>9003.000</td>
</tr>
<tr>
<td>(b_y)</td>
<td>-0.222</td>
<td>0.0283</td>
<td>(b_{s44})</td>
<td>3.234</td>
<td>9003.000</td>
<td>(b_{s38})</td>
<td>-1.179</td>
<td>9003.000</td>
</tr>
<tr>
<td>(b_t)</td>
<td>-0.044</td>
<td>0.0147</td>
<td>(b_{s10})</td>
<td>3.225</td>
<td>9003.000</td>
<td>(b_{s28})</td>
<td>-1.179</td>
<td>9003.000</td>
</tr>
<tr>
<td>(r)</td>
<td>1.008</td>
<td>0.0536</td>
<td>(b_{s20})</td>
<td>3.218</td>
<td>9003.000</td>
<td>(b_{s47})</td>
<td>-1.141</td>
<td>9003.000</td>
</tr>
<tr>
<td>(b_{s39})</td>
<td>-15.065</td>
<td>9029.1000</td>
<td>(b_{s02})</td>
<td>3.108</td>
<td>9003.000</td>
<td>(b_{s37})</td>
<td>1.076</td>
<td>9003.000</td>
</tr>
<tr>
<td>(b_{s45})</td>
<td>-14.509</td>
<td>9017.3000</td>
<td>(b_{s15})</td>
<td>2.985</td>
<td>9003.000</td>
<td>(b_{s27})</td>
<td>1.026</td>
<td>9003.000</td>
</tr>
<tr>
<td>(b_{s26})</td>
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<td>9015.3000</td>
<td>(b_{s09})</td>
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<tr>
<td>(b_{s05})</td>
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<td>(b_{s40})</td>
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<td>9003.0000</td>
<td>(b_{s48})</td>
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<tr>
<td>(b_{s32})</td>
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<td>(b_{s07})</td>
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<tr>
<td>(b_{s14})</td>
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<td>(b_{s46})</td>
<td>-1.961</td>
<td>9003.0000</td>
<td>(b_{s22})</td>
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<tr>
<td>(b_{s16})</td>
<td>4.057</td>
<td>9003.0000</td>
<td>(b_{s30})</td>
<td>1.919</td>
<td>9003.0000</td>
<td>(b_{s36})</td>
<td>0.754</td>
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<tr>
<td>(b_{s43})</td>
<td>3.887</td>
<td>9003.0000</td>
<td>(b_{s21})</td>
<td>1.685</td>
<td>9003.0000</td>
<td>(b_{s11})</td>
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<tr>
<td>(b_{s19})</td>
<td>3.588</td>
<td>9003.0000</td>
<td>(b_{s13})</td>
<td>1.447</td>
<td>9003.0000</td>
<td>(b_{s01})</td>
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<td>9003.0000</td>
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<tr>
<td>(b_{s35})</td>
<td>3.556</td>
<td>9003.0000</td>
<td>(b_{s41})</td>
<td>1.414</td>
<td>9003.0000</td>
<td>(b_{s42})</td>
<td>-0.440</td>
<td>9003.0000</td>
</tr>
<tr>
<td>(b_{s31})</td>
<td>3.535</td>
<td>9003.0000</td>
<td>(b_{s29})</td>
<td>1.399</td>
<td>9003.0000</td>
<td>(b_{s25})</td>
<td>0.273</td>
<td>9003.0000</td>
</tr>
</tbody>
</table>
The point estimate of parameter $b_y$, coefficient of the year variable, agrees with previous models estimating a negative trend with year. However, its magnitude is the highest of any of the models explained before. Its standard deviation, on contrary, is the lowest.

Parameters for dummy variables are listed after parameters for intercept, year, tide and the dispersion parameter of the negative binomial distribution supposed for encounter rate data. They are sorted from highest to lowest absolute values for point estimate. The highest negative values correspond to low density sites in the north (Figure 7) and the highest positive ones to the sites with the highest encounter rates (sites 14 and 32). A concern with this model arises from the extremely high standard deviations estimated for site parameters, which also affects the intercept. High correlations between dummy variables appear to affect the model, which indicates the need to use an alternative approach, as group by lines of sites or zones inside the study area.
Appendix 4. R code used to model trends in vaquita abundance from CPOD data and to produce Table 1 and Figures 10-12.

# This program models vaquita relative abundance
# as thin plate spline fits to Lat & Long,
# and outputs gridded results for the study area.

# This works with R version 2.12.0 and 3.0.1, but the plot export
# only works as bitmap save.
# The plots look best using RStudio with this version of R

library('mgcv')
library(maps)
library(sp)
library(maptools)
library(raster)

# Read CSV files with detection distances and other variables
setwd("e:/")
VaqPodData= read.csv("Vaquita data.csv")  # all delphinid species

# VaqPodData= VaqPodData[VaqPodData$Year!=2011,]  #eliminate first year
# VaqPodData= VaqPodData[VaqPodData$Year!=2013,]  #eliminate last year

summary(VaqPodData)
Lat=   VaqPodData$latitude
Long=  VaqPodData$longitude
ER=    VaqPodData$Encounters
DPM=   VaqPodData$DPM
Site=  as.factor(VaqPodData$Site)
nSite= VaqPodData$nSite
Year=  VaqPodData$Year
CatYear=  as.factor(VaqPodData$Year)
Year2013TF= (VaqPodData$Year==2013)
Tide=  VaqPodData$tide

# Calculate raw trends in mean values of ER and DPM
1-mean(ER[Year==2012])/mean(ER[Year==2011])
1-mean(ER[Year==2013])/mean(ER[Year==2012])
1-mean(DPM[Year==2012])/mean(DPM[Year==2011])
1-mean(DPM[Year==2013])/mean(DPM[Year==2012])

# Conduct GAM EncounterRate analysis using mgcv
VaqPodGam_ER_year= gam(formula= ER ~ Year, family=negbin(theta=c(1.0)), gamma=1.4)
summary(VaqPodGam_ER_year)

VaqPodGam_ER_year_Tide= gam(formula= ER ~ Year + Tide, family=negbin(theta=c(1.0)), gamma=1.4)
summary(VaqPodGam_ER_year_Tide)

VaqPodGam_ER_CatYear= gam(formula= ER ~ CatYear, family=negbin(theta=c(1)), gamma=1.4)
summary(VaqPodGam_ER_CatYear)

VaqPodGam_ER_year_Lat_Long= gam(formula= ER ~ s(Year,k=2) + s(Long,Lat,bs='tp'), family=negbin(theta=c(1)), gamma=1.4)
summary(VaqPodGam_ER_year_Lat_Long)
plot(VaqPodGam_ER_year_Lat_Long,se=FALSE,shade=TRUE,too.far=0.1)
VaqPodGam_ER_year_PolyLatLong_Tide = gam(formula= ER ~ Year + poly(Lat,3) + poly(Long,3) + Tide, family=negbin(theta=c(1), link = "log"), gamma=1.4)
summary(VaqPodGam_ER_year_PolyLatLong_Tide)

VaqPodGam_ER_site_year = gam(formula= ER ~ Site + Year, family=negbin(theta=c(1)), gamma=1.4)
summary(VaqPodGam_ER_site_year)

# Conduct GAM DPM analysis using mgcv
VaqPodGam_DPM_year = gam(formula= DPM ~ Year, family=negbin(theta=c(1,5)), gamma=1.4)
summary(VaqPodGam_DPM_year)
VaqPodGam_DPM_year_Tide = gam(formula= DPM ~ Year + Tide, family=negbin(theta=c(1,5)), gamma=1.4)
summary(VaqPodGam_DPM_year_Tide)
VaqPodGam_DPM_CatYear = gam(formula= DPM ~ CatYear, family=negbin(theta=c(1)), gamma=1.4)
summary(VaqPodGam_DPM_CatYear)
VaqPodGam_DPM_year_Lat_Long = gam(formula= DPM ~ s(Year,k=2) + s(Long,Lat,bs='tp'), family=negbin(theta=c(1), link = "log"), gamma=1.4)
summary(VaqPodGam_DPM_year_Lat_Long)
plot(VaqPodGam_DPM_year_Lat_Long,se=FALSE,shade=TRUE,too.far=0.1)
VaqPodGam_DPM_year_PolyLatLong_Tide = gam(formula= DPM ~ Year + poly(Lat,3) + poly(Long,3) + Tide, family=negbin(theta=c(1), link = "log"), gamma=1.4)
summary(VaqPodGam_DPM_year_PolyLatLong_Tide)
VaqPodGam_DPM_site_year = gam(formula= DPM ~ Site + Year, family=negbin(theta=c(1)), gamma=1.4)
summary(VaqPodGam_DPM_site_year)

# Estimate ratios of mean fitted Values in successive years.
mean2011 = mean(VaqPodGam_DPM_year_Lat_Long$fitted.values[Year==2011 & nSite==30])
mean2012 = mean(VaqPodGam_DPM_year_Lat_Long$fitted.values[Year==2012 & nSite==30])
mean2013 = mean(VaqPodGam_DPM_year_Lat_Long$fitted.values[Year==2013 & nSite==30])
mean2012/mean2011
mean2013/mean2012

# Create Prediction Data Frame over defined study area
minLat = 30.9
maxLat = 31.4
minLong = -114.75
maxLong = -114.40
PredLat = minLat
PredLong = minLong
for (iLat in seq(minLat,maxLat,by=0.005)) {
  for (iLong in seq(minLong,maxLong,by=0.005)) {
    PredLat = c(PredLat,iLat)
    PredLong = c(PredLong,iLong)
  }
}

PredictData2011 = data.frame(Lat=PredLat,Long=PredLong,Year=2011,nSite=32)
DPM_Prediction2011 = predict.gam(VaqPodGam_DPM_year_Lat_Long,newdata= PredictData2011)
ER_Prediction2011 = predict.gam(VaqPodGam_ER_year_Lat_Long,newdata= PredictData2011)

PredictData2012 = data.frame(Lat=PredLat,Long=PredLong,Year=2012,nSite=32)
DPM_Prediction2012 = predict.gam(VaqPodGam_DPM_year_Lat_Long,newdata= PredictData2012)
ER_Prediction2012 = predict.gam(VaqPodGam_ER_year_Lat_Long,newdata= PredictData2012)
DPM_Prediction2011[1:10]
DPM_Prediction2012[1:10]
#NOTE, predictions are additive, exp(predictions) are multiplicative
1-exp(DPM_Prediction2012[1:10])/exp(DPM_Prediction2011[1:10])
(DPM_Prediction2012[1:10]-DPM_Prediction2011[1:10])

# Read study area boundary (see code below to create study area boundary)
StudyArea= readShapePoly(fn="StudyBoundary")

#DPM Geographic Smooth Plots
# Create raster map of predicted values
Predict.dataframe= data.frame(PredLong,PredLat,DPM_Prediction2012)
Predict.raster= rasterFromXYZ(Predict.dataframe)
# Mask areas outside of study area
Predict.raster= mask(x=Predict.raster,mask=StudyArea)
# plot raster
par(mfrow=c(1,1))
plot(Predict.raster, col=rainbow(8))
title("Fitted DPM Model")
# plot(Long,Lat,add=TRUE)
# plot(Predict.raster,add=TRUE, col=gray.colors(8,start=0.1,end=0.8))

#ER Geographic Smooth Plots
# Create raster map of predicted values
Predict.dataframe= data.frame(PredLong,PredLat,ER_Prediction2012)
Predict.raster= rasterFromXYZ(Predict.dataframe)
# Mask areas outside of study area
Predict.raster= mask(x=Predict.raster,mask=StudyArea)
# plot raster
par(mfrow=c(1,1))
plot(Predict.raster, col=rainbow(8))
title("Fitted ER Model")
# plot(Long,Lat,add=TRUE)
# plot(Predict.raster,add=TRUE, col=gray.colors(8,start=0.1,end=0.8))

# Output gridded data of smoothed, modeled Beauf, Lat  Long
# Average.Beaufort= data.frame(endLat,minusEndLong,Prediction)
# names(Average.Beaufort)= c("Latitude","Longitude","Avg. Beaufort")
# write.csv(Average.Beaufort, "C:\Users\Jay\abund\Inferring Gzero\BeaufortGeoSmooth.dat", row.names=FALSE)
# rm(endLat,minusEndLong,Prediction,PredictData)

# Create a study area boundary shape file (only needs to be done once)
# interactive definition of study polygon (USE R, not R studio)
# left click to form polygon then right click and chose stop
plot(Long,Lat)
BoundPoly= drawPoly()
BoundPolyDF= SpatialPolygonsDataFrame(Sr=BoundPoly,data=data.frame("A"))
writePolyShape(BoundPolyDF,fn="StudyBoundary")
Report on Vaquita Rate of Change Between 2011 and 2013 Using Passive Acoustic Data
by the Expert Panel on Spatial Models

June 24-26, 2014
Meeting held at Southwest Fisheries Science Center, La Jolla, CA, USA

Participants:
Armando Jaramillo-Legorreta*
Lorenzo Rojas-Bracho
Jay VerHoef*
Jeff Moore*
Len Thomas*
Jay Barlow*
Justin Cooke*
Tim Gerrodette
Barbara Taylor

*Analysts comprising the Expert Panel
Executive Summary

After reviewing preliminary analysis results from the first three seasons (2011-2013) of the acoustic monitoring program, the Vaquita Acoustic Monitoring Steering Committee recommended that a panel of analytical experts be convened to estimate the trends in vaquita acoustic detections during this period. The Expert Panel1, which met from the 24-26th of June 2014, analyzed these data and estimated a 33% decline in vaquita acoustic activity in the sampled area from 2011 to 2013. This rate of decline, 18.5% per year (95% Bayesian Confidence Interval -0.46 – +0.19 per year), is greater than any previously reported for vaquita. The Panel found a high probability that the acoustic activity has declined (prob. = 0.88) with the clear majority of evidence indicating a rate of decline greater than 10% per year (prob. = 0.75). Other factors, like changes in fishing effort, should be considered for an appropriate measure of uncertainty in trends in vaquita abundance.

The Panel considered the monitoring design to be sound but analyses were complicated by the loss of some monitoring devices (CPODs) in the first year (2011) and low numbers of recording days for numerous CPOD devices in 2013. Several analyses were developed to account for the uneven sampling; all indicated substantial declines similar to the agreed estimate of 18.5% per year. Although the Panel agreed that year-to-year variation in the proportion of vaquitas present within the monitoring area could not be accounted for with this short time series (with only half of the intended monitoring period completed), the chances that this critically endangered species has continued to decline at a high rate are great.

---

1 The panel consisted of 6 modeling experts including two from the Vaquita Acoustic Monitoring Steering Committee (Jaramillo and Barlow) and four globally recognized
Introduction

In 2011, the passive acoustic monitoring program for vaquitas (*Phocoena sinus*) began the first full season of data collection. In April 2014, the Vaquita Acoustic Monitoring Steering Committee (SC) met to review data from the first 3 seasons of data (2011, 2012, 2013). Preliminary analysis suggested a dramatic decline in the vaquita population between 2011 and 2013 (Jaramillo-Legorreta et al. 2014). However, because the realized sampling effort was uneven across the sampling grid and over each sampling season, analysis of the data was not simple. Therefore, the SC recommended that a panel of experts with specific skills in spatial or trend modeling be convened to provide the best scientific analysis of trends in abundance of vaquita acoustic detections in a timeframe needed to manage this critically endangered species. The expert Panel was formed and met at the Southwest Fisheries Science Center in La Jolla, California, on June 24-26, 2014. This document reports the findings of the meeting.

Background

The vaquita is a small species of porpoise found only in the northern Gulf of California, Mexico (Figure 1). It is subject to unsustainable bycatch in gillnet fisheries throughout its small range and, consequently, is classified as critically endangered by the International Conservation Union (IUCN). Although they are known to occur in waters 10-50 m deep, their distribution within the shallow water area is poorly characterized. The vaquita detections shown in Figure 1 are not fully representative of distribution in shallow water areas because most sightings are from a ship that cannot navigate shallow waters (see tracklines in Figure 1). The polygon within the figure is the Vaquita Refuge, which was agreed to in September 2005 (Protection Program published on December 2005) and within which no commercial fishing is allowed (no matter what fishing gear is used, even hooks). About half of vaquitas are estimated to be in the Refuge at any given time (Gerrodette and Rojas-Bracho 2011). Surveys in different years (1997 and 2008; Jaramillo-Legorreta et al., 1999; Gerrodette et al., 2011) suggest that for the months of surveys (most from August through November) the distribution of vaquitas is remarkably constant. Within the Refuge, vaquitas are unevenly distributed.
Figure 1. Visual detections (red and green circles) from two major ship surveys (in 1997 and 2008), with the survey track lines shown as light gray lines. The C-POD locations (deployed regularly since 2011) are shown as black dots and the Vaquita Refuge is outlined in black.

Because of the expense and imprecision of visual surveys (Jaramillo Legorreta, 2008; Rojas-Bracho et al., 2010), Jaramillo pioneered acoustic monitoring for vaquitas starting in 1997. Acoustic monitoring is possible because porpoises use echolocation to find their prey in the turbid waters of the northern Gulf of California. Jaramillo deployed boat-based acoustic detectors at fixed listening stations located throughout the range of vaquitas to examine the change in acoustic encounters over a period of 11 years (1997-2008) and showed a marked decline of 7.6%/year for a total decline of 58% (Jaramillo-Legorreta 2008). By the end of this study most stations recorded no vaquita acoustic activity and it became obvious that the level of acoustic monitoring effort achieved during the initial years of research were no longer sufficient to monitor vaquita activity accurately.

Thus, in 2008 several types of bottom-mounted passive acoustic devices, which are capable of recording autonomously for several months, were tested to increase the acoustic sampling effort for the dwindling numbers of vaquitas. A device called the CPOD had the best performance (Rojas-Bracho et al. 2010). The CPOD records characteristics of acoustic activity continuously over a period of several months. A Steering Committee (SC) was formed to design an acoustic monitoring project capable of detecting a ≥4%/year increase over a 5 year period (which would include 6 monitoring seasons). The SC created a grid design using 48 bottom-mounted CPODs deployed inside the Refuge for about 90 days each year. The original
monitoring design also included CPODs located on Refuge perimeter buoys, but these CPODs were nearly all lost due to entanglement with fishing gear and likely active removal. A feasibility project was conducted using bottom-mounted CPODs just outside the southwestern boundaries of the Refuge but 6 of 8 were lost indicating that this area is still not possible to monitor with fixed CPODs (Jaramillo-Legorreta 2014).

After 2 years of initial testing and development, the acoustic monitoring program began its’ first full season in 2011. The deployment and recovery of the bottom-mounted grid of CPODs was very successful over the first 3 seasons. However, the number of days recorded by individual CPODS differed because some CPODs were lost and never recovered, others shut off early within a season, and some filled their memory with background noise prior to retrieval. Figure 2 illustrates the achieved acoustic monitoring effort (i.e., days of acoustic monitoring per C-POD station) for the first 3 years.

![Figure 2](image)

*Figure 2. Locations of sampling sites, with number of days of monitoring effort indicated by circle size.*

Effort also differed seasonally within year. CPODs were deployed later in 2012 and 2013 than in 2011 to avoid CPOD loss resulting from fishing activities (Figure 3), and deployment date now depends on information from aerial surveys that illegal fishing activities within the Refuge have largely ceased.
Estimating the change in numbers of vaquita acoustic detections from 2011 to 2013 required an analytical treatment that accounts for the spatial and temporal differences in sampling within and between years, as shown in Figures 2 and 3. Conceptually, the analytical task is to best approximate the results that would have been obtained if all the circles in the grid shown in Figure 2 of were of equal size each year (same level of CPOD effort at all stations in all years). To do that, the Panel needed to consider all the factors that may make effort unequal and decide the best method of inference for stations that were un- or under-represented. In addition, the Panel needed to consider other factors besides differences in vaquita abundance or activity that may have caused differences in detections between years.

Figure 3. Effort by Julian day for each year. Julian dates shown run from May 30 (150) to October 2 (275). Vertical red lines enclose the core sampling period (from Julian day 170-231, June 19 to August 18, where ≥ 50% of the CPODs were operating in all years (discussed below). Julian dates actually vary slightly because of leap year.
The simplest approach to measuring trends in vaquita clicks from C-POD data is to calculate the ratio of total clicks counted in 2011 to the total number in 2013. However, this approach does not account for C-PODs that were lost or C-PODs that were not functional for the entire core sampling period. If C-PODs were lost predominately in high-density areas (which appears to be the case in 2011), this simple approach would produce biased estimates of trends. Likewise, if some sites received less effort, the total counts should be standardized to the number of days sampled, to avoid bias. To avoid both of these problems, analysis can be limited to data from sites that were sampled in all three years, and the mean number of clicks per day of sampling effort could be calculated for all these common sites. This direct-count method was used to produce estimates for comparison with other, better methods, which use more of the data (including data from sites that were only sampled in one or two years) and provide statistical estimates of uncertainty about the true trend given the data. The direct-count method does not make any estimate of certainty about the true trend but rather relies on an assumption that the data perfectly represent the true trend.

In contrast with the direct-count method, the Panel conducted statistical analyses that use spatial and temporal information within the dataset to estimate the probability that the acoustic data could have been observed by chance alone (noting that the data are a sample rather than perfect measurement of what we want to estimate) and to obtain a better estimate of trends that reflects uncertainty about the true trend for the population. The expert panel was directed to find the best method of statistical analysis to account for uncertainty and to make optimal use of all the available data.

Considerations from the Expert Panel

The primary objective of the Panel was to estimate the annual mean rate of change in numbers of vaquita acoustic detections from 2011 to 2013 together with any uncertainties in that rate. A necessary assumption for analysis was that the annual rate of change in acoustic detections is a reasonable proxy for the rate of change in vaquita numbers. There are several important factors to keep in mind when interpreting the trend estimates from these first 3 years of acoustic detections.

First, if the monitoring grid covered the entire distribution of vaquitas, then inference about change in total vaquita population abundance would just depend on the assumption that click behavior remained the same through the time period (i.e., more recorded clicks would imply more vaquitas, not just more vocalizing, in the sampling area). Click behavior was investigated and there was no evidence of a change in clicks-per-vaquita in different years (see below). Additionally, there are data from past efforts covering the full range of vaquitas that support the assumption that acoustic detections and numbers of vaquitas decline at the same rate. For example, between 1997 and 2008 visual surveys and acoustic monitoring
resulted in identical estimates of rate of change with a decline of 7.6%/year (Gerrodette et al. 2011, Jaramillo-Legoretta 2008). Therefore, the assumption that the number of recorded clicks is related to the level of use in the sampling area was judged to be reasonable.

Second, intense fishing outside the Refuge, even in the low summer fishing season, precludes using bottom-mounted CPODs outside the Refuge. Because the grid covers only a proportion of the vaquitas range, the other important assumption is that the proportion of vaquitas using the monitoring area over the summer period is the same each year. Over the 6-sampling seasons that the monitoring program was designed to cover, the changes in proportion in the Refuge would be expected to vary somewhat from year to year but not in any systematic way that would bias the rate-of-change estimate. However, with just three seasons of data (two periods of change), there is greater uncertainty about how much of the estimated annual change reflects change in overall population abundance vs. differences in the proportion of population using the sampling area each year. The length of the sampling period within a year mitigated this variability somewhat, but the Panel recognized these limitations to inference from the analysis. Additional years of data will allow this issue to be addressed analytically.

Panelists agreed that the design of the monitoring program, which has systematic spatial coverage throughout the core of the Vaquita Refuge (and central to the distribution of the species) over a period of several months each year, was good, and that the analysis should rely primarily on this good design rather than on model-based spatial or temporal extrapolation to unsampled areas. The Panel carried out some basic descriptive analyses to consider factors other than a change in the number of vaquitas that might affect the number of acoustic detections observed.

**Time of day:** Because CPODs record data 24 hours per day and only whole days are used in the analysis, the sampling design is balanced with respect to time of day. The Panel agreed that analysis could proceed without accounting for the influence of time of day on the data.

**Tide:** The northern Gulf has a tidal range of over 10m (30 feet), which has potential to influence vaquita behavior and therefore acoustic detections. Therefore, the sampling of tidal states should be similar in different years if analyses are conducted without accounting for sampling of tidal states. Jaramillo stratified the data into different tidal states. The tidal regime in the Upper Gulf of California is semidiurnal (two high and two low tides per day) and a cycle of spring-neap tides last approximately 15 days. Instead of using tide height as presented in tide tables, Jaramillo calculated the vertical speed of tide per hour as an index of tide current (using the tide height at the current hour minus the tide height at the previous hour). The absolute value was used, which does not distinguish between flood or ebb tides. Coverage of tidal states was similar between years (Table 1, 0.1 meters/hour intervals). A Kruskal-Wallis ANOVA by ranks indicated that the samples of every year originated from the same distribution, $H_{df\,2,\,n=4464}=3.285,$
p=0.1934. A median test gives similar non-significant results (Chi-squared=1.2, d.f.=2, p=0.5491). The Panel agreed that analysis could proceed without accounting for the influence of tides on the data.

Table 1. Number of hours sampled in eighteen vertical tide speed intervals for each sampling year period (2011-2013).

<table>
<thead>
<tr>
<th>Tide speed interval</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>≥ 0.0</td>
<td>≤ 0.1</td>
<td>151</td>
<td>150</td>
</tr>
<tr>
<td>&gt; 0.1</td>
<td>≤ 0.2</td>
<td>153</td>
<td>156</td>
</tr>
<tr>
<td>&gt; 0.2</td>
<td>≤ 0.3</td>
<td>159</td>
<td>160</td>
</tr>
<tr>
<td>&gt; 0.3</td>
<td>≤ 0.4</td>
<td>151</td>
<td>133</td>
</tr>
<tr>
<td>&gt; 0.4</td>
<td>≤ 0.5</td>
<td>125</td>
<td>134</td>
</tr>
<tr>
<td>&gt; 0.5</td>
<td>≤ 0.6</td>
<td>139</td>
<td>126</td>
</tr>
<tr>
<td>&gt; 0.6</td>
<td>≤ 0.7</td>
<td>121</td>
<td>115</td>
</tr>
<tr>
<td>&gt; 0.7</td>
<td>≤ 0.8</td>
<td>106</td>
<td>117</td>
</tr>
<tr>
<td>&gt; 0.8</td>
<td>≤ 0.9</td>
<td>99</td>
<td>90</td>
</tr>
<tr>
<td>&gt; 0.9</td>
<td>≤ 1.0</td>
<td>73</td>
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<tr>
<td>&gt; 1.7</td>
<td>≤ 1.8</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Seasonal Effects: The Panel considered whether shifts in the amount of acoustic activity of vaquitas throughout the sampling season (generally from June through early September) could affect estimates of rate of change (see Appendix 3 for raw click data for each station and in each year). The distribution of sampling effort over the sampling season, as well as the pattern of apparent acoustic activity, differed somewhat among years (Figure 4). To avoid any potential biases caused by these differences, the Panel decided to analyze a seasonally reduced dataset that included dates chosen to be those within which at least 50% of the CPODs were operating across all 3 years, i.e., from Julian day 170-231 [June 19 to August 19]. This core sampling period included 76.3% of the data, henceforth called the core dataset. The Panel used a Generalized Additive Model (details in Appendix 2) to assess whether the results from truncated dataset differed from using the full dataset (excluding data after September 14, the day prior to the earliest opening of shrimp season over the three years). This sensitivity test showed there were seasonal differences. This affirmed the choice to use the core dataset in order to avoid confounding inter-annual differences in seasonal sampling with potential seasonal differences in vaquita distribution. After discussion about whether it was necessary to model time
within year (e.g., month), the Panel agreed that, for the purpose of estimating overall annual rate of change, using a common season across years and pooling data across that core period within a year would deal adequately with seasonal effects. The Panel agreed that analysis could proceed using the core dataset and by averaging acoustic data within a year for each sampling point.

Figure 4. Mean acoustic detection positive minutes (see next section – Acoustic metric – for explanation), averaged across CPODs (y-axis) for each day of sampling (x-axis). Each dot represents a single day of sampling, with dot size proportional to the number of CPODs operating on that day. The red curves represent a smooth (a generalized additive mixed model with separate thin plate regression spline smooth per year, normal errors, identity link, weights that are number of CPODs and auto-regressive error structure of order 1) with approximate 95% confidence interval shown as dashed lines. Vertical red lines indicate the core sampling period from Julian day 170-231.
Acoustic metric: The Panel focused its discussion on two types of measures of vaquita acoustics: clicks/day and detection positive time units (see below for discussion of appropriate time unit). Using acoustic events such as clicks/day to estimate trends in vaquita abundance assumes that acoustic events have a constant relationship with the number of vaquitas. Clicks are the most direct form of the acoustic data, and Panelists agreed that clicks/day would be the preferred metric as long as the statistical properties were acceptable. However, Panelists thought it useful to examine the data to see whether the amount of clicking per vaquita might have differed each year (e.g., due to annual differences in prey availability within the sampling area). The number of clicks per Detection Positive Minute (DPM, which is any minute that includes vaquita clicks) was variable, but with a similar pattern between years (Figure 5), which increased confidence in using clicks/day as a reliable acoustic index of vaquita abundance. Additionally, clicks/day was well characterized using a negative binomial distribution in generalized additive models (GAMs) and had no statistical issues in other models used (see details below and in Appendix 2). Nevertheless, the Panel thought analysis using a second metric that would be potentially less sensitive to changes in acoustic behavior would be useful as a sensitivity analysis. In addition to using DPMs, another metric explored was the number of times vaquitas were present (“positive”) or not within a time unit that contained most vaquita encounters, where an encounter is determined as a period of detected activity (clicks) defined by silent gaps at each end of more than 30 minutes). The Panel considered different time units, and chose 30 minutes because just over 90% of vaquita encounters were less than 30 minutes in duration (Figure 6). These encounter units are called Detection Positive Half Hours (DPHH). The metric of vaquita positive 30-minute periods was thus used to examine the robustness of the results based on clicks/day.

Figure 5. The number of clicks per Detection Positive Minute (DPM) over time.
The relationship between number of DPMs per encounter and encounter duration appears to be linear, although with high variability (Figure 7). Thus, rates of echolocation (as indicated by slope) are nearly constant with increasing encounter duration. Different colors are shown for the three years (red, black and blue respectively from 2011-2013). No differences between years are apparent.
The GAM models using a negative binomial distribution had a poorer fit using either DPMs or Detection Positive Half Hours (DPHH) per day than using clicks/day (detailed below and in Appendix 2). The DPHH also tended to become saturated (Figure 8). An aggregation of 2 vaquitas could produce similar values of DPM and even more similar values of DPHH as an aggregation of 5 vaquitas, whereas total clicks would be expected to increase more linearly with average group size. This topic is further discussed below under the Spatial GAMs Model.

![Figure 8. A loess smoothed fits of the number of detection-positive minutes (DPMs) per day (left) and the number of detection-positive half hours (DPHH) per day (right) as functions of the number of vaquita clicks per day for each site and year. Data are limited to the core sampling period.](image)

The Panel agreed that the metric of choice was clicks/day because this metric uses the most raw form of the data and no statistical issues preventing its use.

**Agreed scope of inference:** The Panel discussed at length the types of analyses that could be performed on the data, and the inferences that could be drawn from the results.

1. **The Panel agreed that the spatial scope of inference should be limited to the CPOD sampling locations.** In other words, predictions from all models would be made only at the sample locations; no attempt would be made to extrapolate the predictions to some wider area such as the entire refuge. Such extrapolations cannot reliably be made from spatial models that omit biologically-relevant explanatory variables; in the present case constructing a detailed spatial habitat model would take far longer than the time available.

2. **Estimates would only be made covering the core sampling period, where at least 50% of the CPODs were operating in all years.** Any analysis would need to account for the fact that some locations did not have CPODs operating for the full time period in each year; data from each location and year should be weighted by the number of sample days.

3. **Inference from the analysis would be based on model-predicted click counts from the model at all sampled locations (n = 45).** An alternative would have been to predict click counts only at locations with no sampling
effort in a particular year, and to use observed click counts at the other locations for making between year comparisons; this approach was rejected firstly because of the uneven number of sampling days across locations (higher sampling error and thus less confidence that the raw data accurately represent activity levels at less frequently sampled locations) and secondly because the observed click counts are extremely variable, likely reflecting variations in vaquita behavior in the vicinity of the CPODs (e.g., variation in animal speed, foraging behavior, etc.) – it was felt that using a model to “smooth out” this variability would result in more reliable inference about trend and provide a better assessment of the uncertainty associated with an estimates.

**Description of Models**

The Panel agreed to use Bayesian inference approaches for the main models used to estimate rate of change. There are many advantages of using Bayesian methods, but of particular value in the current context was the desire to obtain posterior probability distributions for annual rate-of-change, which in turn allow for straightforward estimation of the probability that the population declined between 2011 and 2013.

After consideration of numerous models, the Panel focused on two models with differing assumptions: the Spatial Model and the Non-Spatial Mixture Model. Here we describe the basis for these models with details in Appendix 2.

**Spatial Model Description**

The spatial model smoothed over the observed data, considering them to be a noisy version of an underlying smooth pattern of vaquita use. Vaquitas move throughout the study area, and the number of clicks encountered at a station are considered as an imperfect sampler due to stochastic movements of vaquitas. There is also unequal effort at locations, with some locations completely unsampled in some years. The model partitions variability into a spatially smooth surface plus independent random error, where the variance of the independent part decreases proportional to effort (number of sampling days). The estimated surface of vaquita use, then, is the predicted spatial surface. Each year is treated independently for predictions, but autocorrelation parameters are estimated by pooling across years.

The spatial model was a Gaussian log-linear mixed model (i.e., data assumed normal on log scale) with spatially autocorrelated error structure. Rationale for using this approach in favor of others is discussed below (see *Basis for model choice*). Details of this model are in Appendix 2. An overview is provided here.

The response variable data \(W_{ti}\) were the average number of clicks detected per day at each CPOD location \(i\) within a sampling year \(t\). Thus the sample size for analysis was the sum of the number of CPODs functioning during the core sampling
period in each year; this totaled 128 “CPOD-years”. The data were transformed by adding 1 and taking the log of the values, i.e., $Y_0 = \log(W_0 + 1)$, because some functioning detectors recorded zero clicks during some years. The transformed data had reasonable variance:mean properties for using a Gaussian model (Appendix 3).

The transformed data were thus fit by the following model:

$$Y_{ti} \sim \text{Normal}(\mu_t + Z_{ti}, \sigma^2 / n_t),$$

where $\mu_t$ is the expected mean number of clicks per day across locations in year $t$, $Z_{ti}$ is a spatially autocorrelated random effect allowing the number of clicks per day at each location within a year to depart from the overall mean (with CPODs in closer proximity to each other expected to have more similar departures from the overall mean), and $\sigma^2$ is the variance for spatially independent random error, weighted by variable sampling effort (number of CPOD-days, $n_{ti}$) across locations.

Details for estimating the spatial component of the model ($Z_{ti}$) are in Appendix 2. Worth noting here is that years were treated independently in the model, such that a different spatial surface was estimated from each year’s data, but all years were assumed to have the same autocorrelation structure (same exponential decay in spatial random effect covariance as function of distance between locations). Also note that the spatial model is used to provide predictions for $Y_{ti}$ at all $K$ CPOD locations ($K = 45$), including those not sampled in some years, by drawing on information (through the spatial model parameters) from surrounding CPODs.

Inference was based on several summaries derived from the model parameter posterior distributions. Let $S_{ti}$ be the predicted values for the average number of clicks per day (smoothed over the noisy process with variance $\sigma^2$), back-transformed to the original scale of the data,

$$S_{ti} = \exp(\mu_t + Z_0) - 1$$

An index of abundance ($B_t$) is taken to be the average of these values across all $K$ CPOD locations for each year. Thus, given fitted estimates (predicted values) for $S_{ti}$:

$$B_t = \frac{1}{K} \sum_{i=1}^{K} S_{ti}.$$  

An estimate of the geometric mean annual rate of population change between 2011 and 2013 is calculated as $\lambda = (B_{2013}/B_{2011})^{1/2}$. The proportion of the posterior distribution for this quantity that is less than 1 provides an estimate for the probability that the population in the sampled area has declined between 2011 and 2013.
Posterior summaries including means, medians, variances and credible intervals were obtained from MCMC samples. MCMC specifications (including priors) are detailed in Appendix 2.

**Non-spatial Mixture Model Description**

The non-spatial mixture model draws on the strength of the sampling design (repeat samples from a fixed semi-regular grid throughout the study area). Predicted click levels at individual CPOD locations were not based on a spatial model. Rather, within a generalized linear mixed model framework, individual CPOD locations were assigned probabilistically to one of \( V = 3 \) groups based on the level of detections they received across multiple years of sampling. Predictions for individual locations are given by estimated means and random effect variances for the groups to which CPOD locations are attributed.

The parameter of interest is \( \theta_{v[k],t} \), the mean click rate (clicks/day) in year \( t \) for each of the \( V \) groups to which detector \( k \) is attributed. Because the data (total clicks per location per year, \( n_{kt} \)) were overly dispersed for a Poisson model, they were treated as negatively binomially distributed with the expectation given by the product of the estimated \( \theta_{v[k],t} \) and effort (number of CPOD days, \( d_{kt} \)), i.e.,

\[
n_{kt} \sim \text{Negative Binomial} \left( p_{kt}, r_{v[k],t} \right),
\]

where \( p \) and \( r \) are negative binomial parameters, and where \( \mu_{kt} = \theta_{v[k],t} d_{kt} = r_{v[k],t} (1 - p_{kt})/p_{kt} \) gives the expectation for \( n_{kt} \). Thus, variable sampling effort across CPOD locations is handled through its effect on the expectation and variance for \( n_{kt} \).

Exploratory generalized additive model (GAM) analysis suggested that the click-rate data were well described by a negative binomial error distribution (see below).

Individual CPODs were probabilistically assigned to a use-intensity group \( v \) based on the data recorded at \( k \) across the years during which CPOD \( k \) was functioning. In OpenBUGS (Bayesian analysis software), this was done using the “categorical distribution” (multivariate generalization of the Bernoulli):

\[
v[k] \sim \text{cat}(s_{vk}),
\]

where \( s_{vk} \) is the vector of estimated probabilities for \( k \) being in group \( v \), which come from a Dirichlet prior distribution (see details in Appendix 2). The degree of certainty in assigning a CPOD location to a particular group depends on how correlated detections were through time; sites with consistently low or high levels of detections are assigned to a group with greater confidence, and all else being equal, CPODs with 3 years of data are assigned more confidently to a group that sites with one or two years of data. Uncertainty in group assignment is propagated through to estimates of other parameters.
In short, the number of detections recorded across all CPODs are assumed to arise from a mixture of \( V \) negative binomial distributions. Information across years is shared for the purpose of assigning each CPOD location to a particular group \( v \), but the means and variances for each \( v, t \) are independent. Predicted estimates for CPOD locations in years with missing data are based on the probability of belonging to group \( k \), and the conditional mean and variance for group \( v \) in year \( t \).

Inference is on the overall mean values for daily click rate (\( M_t \)), which are simply the means of the \( \theta_{v[k],t} \) weighted by the number of CPODs belonging to each group \( v \), for each \( t \), i.e., \( M_t = \frac{1}{K} \sum_{k=1}^{K} \theta_{v[k],t} \). The rate of change between 2011 and 2012 is \( M_2/M_1 \). The rate of change between 2013 and 2012 is \( M_3/M_2 \). The mean annual rate of change, \( \lambda \), is the geometric mean of these two values. The probability that the population declined from 2011 to 2013 is the proportion of the Bayesian posterior distribution for \( \lambda \) that is less than 1. Inference about population change is based on posterior distribution summaries for these derived parameters.

**Spatial GAM Models**

In addition to the models used to estimate the rate of change, the Panel agreed that a frequentist approach would be useful for efficiently exploring the potential sensitivity of analysis results to some of the Panel’s modeling decisions, such as the choice of acoustic metric. However, GAMs were not favored by the Panel as the approach for making inference because GAMs do not provide posterior probability estimates for key parameters of interest.

During the workshop, Generalized Additive Models (GAMs) were developed to quickly evaluate and compare alternative models for estimating population change before implementing those models in Bayesian spatial models. In the GAMs, year was treated as a categorical explanatory variable (2011, 2012 and 2013) and spatial variation was modeled as a two-dimensional thin-plate spline using the \textit{mgcv} package in R. It was assumed that the spatial distribution of vaquitas were the same across years. GAMs that estimated different spatial patterns for each year were generally not stable and are not reported here.

The primary purpose of using GAMs was to test different dependent variables, different error structures, and different mean/variance relationships. Population rates of change were based on mean GAM predictions for the entire set of 45 sampling stations from 2011 to 2013. Additional details on the GAMs are given in Appendix 2.

**Basis for model choice**

The Panel’s charge was to give a best estimate of the current rate of change in vaquita detections. Although the spatial and mixture models gave similar results
(see below), the Panel carefully considered the merits of each. Below we summarize the main differences between the two approaches.

- The spatial model assumes that the spatial distribution of clicks is different each year but uses multiple years to estimate the spatial auto-correlation. The non-spatial mixture model assumes that each site falls (probabilistically) into categories of high, medium or low density and that the probability of membership in these categories is shared between years for a given site.

- The spatial model uses information on site location to smooth over random spatial variations in density. The non-spatial model uses no information on site location or proximity between sites.

- The spatial model assumes that the logarithm of mean clicks per day is normally distributed and the non-spatial model assumes that total click counts have a negative binomial distribution.

The Panel agreed that both approaches had merit and that averaging results of the two models would form the best basis for estimating rate of change.

Results and Discussion

Trends in vaquita clicks were first measured using the direct-count method, based only those sites that were sampled in all years (n=39). The direct-counts indicated a total change in the number of recorded clicks of -41% from 2011 to 2013 which is an annual rate of -23.1% per year (negative changes are declines). However, as discussed previously, this method may be biased by non-random survey effort in space and time, and additionally does not provide any estimate of certainty in the true rate of change.

The exploratory GAM analysis showed that total clicks for each site and year could not be adequately modeled with common distribution functions (Poisson, negative binomial and Tweedie distributions). However, the negative binomial distribution provided a very good fit to mean clicks per day for each site and year (Appendix 2), and this distribution was used for subsequent analyses. An analysis with the entire summer dataset was compared to one based only the core sampling period (when at least 50% of CPODS were active in all years). Results showed that click rates trends differed for these two approaches. Of the two, the Panel decided to conduct remaining analyses and base inferences on the core sampling period data, to avoid potential biases caused by unbalanced spatial and temporal coverage in the full dataset (also see Seasonal Effects Section above).

GAM analyses were also used to explore two alternative acoustic measures of vaquita relative abundance: the mean number of minutes per day with vaquita clicks present (detection positive minutes – DPM) and the mean number of half-
hour periods per day with vaquita clicks present (detection positive half-hours – DPHH). A negative binomial distribution function was used in a model that fit a common spatial pattern for all years. Results showed that the mean rates of decline for these two metrics (Table 2) were qualitatively similar to declines estimated using the Bayesian spatial model and non-spatial mixture model, but the model fit was not as good as with mean clicks per day (Appendix 2). DPM and DPHH only indicate the presence of vaquitas during a fixed time period and do not indicate the number of animals present. The vaquita distribution is very patchy, and these metrics tend to saturate at higher click count values (Figure 8) and are not thought to provide as much information on relative abundance as the number of clicks. An aggregation of 2 vaquitas might produce similar values of DPM or DPHH as an aggregation of 5 vaquitas. This could explain why the estimated rates of decline for these metrics are less than for the metric based on number of clicks.

**Table 2. Estimated annual rates of change estimated from Generalized Additive Models using three different acoustic metrics (see Appendix 2 for details). Confidence limits (CL) are based on analytical estimates of standard error.**

<table>
<thead>
<tr>
<th>Acoustic Metric</th>
<th>Sampling Unit</th>
<th>Annual % Rate of Change</th>
<th>Lower 95% CL</th>
<th>Upper 95% CL</th>
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</thead>
<tbody>
<tr>
<td>Mean Clicks/day</td>
<td>Yearly mean for each site</td>
<td>-27.2</td>
<td>-43.3</td>
<td>-6.6</td>
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<tr>
<td>Mean DPM/day</td>
<td>Yearly mean for each site</td>
<td>-20.7</td>
<td>-37.3</td>
<td>+0.2</td>
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<tr>
<td>Mean DPHH/day</td>
<td>Yearly mean for each site</td>
<td>-19.1</td>
<td>-36.2</td>
<td>+2.5</td>
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<tr>
<td>Total DPHH</td>
<td>Daily total for each site</td>
<td>-26.1</td>
<td>-30.6</td>
<td>-21.2</td>
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</table>

In summary, the GAM analyses proved valuable for quickly evaluating the sensitivity of model results to the choice of dataset (affirming choice to use only the core sampling period), acoustic metric (affirming choice to use clicks rather than more aggregated measures), and assumed error distributed (affirming need to model log-transformed data or assume a negative binomial error structure in the case of the non-spatial mixture model). The Panel agreed that mean clicks per day was likely the most sensitive and proportional to changes vaquita abundance. Note that these models assume that the spatial distribution of vaquitas is the same in all three years, and thus differ from the Bayesian spatial model in this respect.

The Panel agreed to use the pooled posterior distributions from both the spatial model and the non-spatial mixture model and to use posterior means as the central estimate. The average trend estimated from the spatial model is a change of -17.5%.
per year with a 95% posterior credibility interval from -50% to +26% per year, and the posterior probability of decline is 0.86. The estimated spatial density of vaquitas from the spatial model is illustrated in Figure 9, and the full posterior probability distribution is illustrated in Appendix 2. For the non-spatial mixture model, the average trend is a change of -19% per year. This non-spatial model gave a narrower 95% posterior credibility interval (from -43% to +13% per year, see Appendix 2 for the full posterior probability distribution) and a higher posterior probability of a decline (0.91). Results of these two models are averaged by drawing equally from their respective Bayesian posterior samples for the growth rate parameter. The model-averaged estimate for population change (Figure 10) has a mean of -18.5% per year and a 95% posterior credibility interval from -46% to +19% per year. The posterior probability of decline is 0.885 and the probability that the decline is greater than 10% per year is 0.753.

Figure 9. Estimated mean number of clicks per day predicted by the spatial model for the 45 C-POD sites with data for at least one year. Values are posterior medians. Sites with a circle/cross were missing in the indicated year. The analysis did not constrain the density surface to be the same each year.
Figure 10. Posterior probability distribution from the pooled spatial and non-spatial mixture models. The mean is a -18.5% change (decline) per year.

The Panel agreed that the estimated rate of -18.5% should be considered as the best estimate of current rate of decline from the acoustic data alone. The Panel agreed that the uncertainty about this rate using only the acoustic data from 2011-2013 does not accurately reflect the actual uncertainty about the current decline of vaquitas because the analyses done in this report do not consider factors like known recent rates of decline and changes in the level of fishing effort. The 2.5% and 97.5% tails of the posterior distribution imply a nearly 50% annual decline for the lower limit and a 19% per year growth for the upper. This upper value is not credible as a population growth rate for vaquitas given the theoretical maximum growth rate for this species (less than 4% growth per year, Hohn et al. 1996) and given recent trends in fishing effort (minutes to the 3rd meeting of the Presidential Commission on Vaquita, September 26, 2013). The Panel recommends that the analyses conducted here using only the acoustic data from 2011-2013 be used in a population growth model that accounts for these other factors and better characterizes uncertainty in the rates of decline.
Acknowledgements

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Literature Cited


Appendix 1: Brief biographies of the Expert Panel

Dr. Armando Jaramillo-Legorreta was raised in Mexico City and received his bachelor's degree at La Paz, Baja California Sur with a focus on marine biology. His main research interest since 1986 has been in the study of ecology and dynamics of marine mammal populations. He received his Masters and PhD degrees in Baja California with a research focuses on coastal oceanography, population ecology and population dynamics modelling. From 1996 to the present day, he is a researcher for the Marine Mammals Research and Conservation Group of the National Institute of Ecology in charge of the study of habitat use and acoustic monitoring of vaquitas. He was the lead author of the first estimate of abundance of vaquitas in 1997 and the first acoustic monitoring between 1997 and 2008 that informed Mexican Government of the decline of vaquita population. Since 2009 has led the current acoustic monitoring scheme. He has coauthored about 20 papers and chapters on different aspects of marine mammals as well as many technical reports. He is delegate for Mexico at the Scientific Committee of the International Whaling Commission and an advisor on the Mexican National Commission for Biodiversity. He is the current President of the Mexican Society of Marine Mammals.

Dr. Jay Barlow is a research scientist within the Marine Mammal and Turtle Division, SWFSC, La Jolla, where he has worked for 32 years. Jay received his PhD from Scripps Institution of Oceanography (SIO) in 1982. He is the leader of the EEZ Marine Mammals and Acoustics Program within PRD and is an Adjunct Professor at SIO. Dr. Barlow’s research involves assessing human impacts on marine mammal populations, estimating their abundance and dynamics, the understanding role of mammals in marine ecosystems, and developing survey methods that use passive acoustics to detect and localize cetaceans. He currently is advisor of three PhD students and serves on dissertation committees of four others. At SIO, Jay teaches a 4-unit course called “Computer-intensive Statistics”. Jay serves on many advisory committees both within NOAA (e.g., the NMFS Steering Committee on Assessing Acoustic Impacts on Marine Mammals and the Humpback Whale Biological Review Team) and internationally (e.g., the IUCN Cetacean Specialist Group). Jay has authored or co-authored 110 peer-reviewed journal articles and book chapters, 75 numbered government reports, and edited one book. He has been chief scientist on 12 NOAA and one Australian research surveys.

Dr. Jay VerHoef began his career as a statistician with the Alaska Department of Fish and Game, after receiving a co-major Ph.D. in statistics and ecology and evolutionary biology from Iowa State University. He now works as a statistician for a research lab, the National Marine Mammal Laboratory within the National Marine Fisheries Service of NOAA. For over 25 years, Dr. VerHoef has developed statistical methods and consulted on a wide variety of topics related to plant, animal, and environmental statistics. Dr. VerHoef is a fellow of the American Statistical Association (ASA) and past-Chair of the Section on Statistics and the Environment of ASA. He has over 100 publications, and he is a co-author of a book on spatial statistics. His CV can be found here

https://sites.google.com/site/jayverhoef/Home/cv
Dr. Jeff Moore is a research scientist within the Marine Mammal and Sea Turtle Division of the NOAA Southwest Fisheries Science Center in La Jolla, California, where he has worked for five years. Jeff has B.Sc., M.Sc., and Ph.D. degrees in Wildlife Biology from UC Davis, Humboldt State, and Purdue University. Prior to coming to SWFSC, Jeff held post-doc and research faculty appointments at Duke University for four years, where he worked on a global fisheries bycatch assessment for marine 'megafauna' and developing methods for quantifying population impacts of bycatch on long-lived species, and for assessing interactions between developing country small-scale fisheries and coastal marine mammals and sea turtles. Jeff’s current research involves assessing human impacts on marine vertebrate populations, estimating abundance and population dynamics parameters using Bayesian statistical methods, and developing quantitative tools to aid management and policy decisions. Jeff serves on advisory committees such as the Biological Review Team for reviewing the status of northeastern Pacific white sharks, and the IUCN Cetacean Specialist Group. He has authored or co-authored > 30 peer-reviewed scientific journal articles since 2004 (3/yr) in addition to numerous NOAA agency technical reports.

Dr. Len Thomas is a senior faculty member within the School of Mathematics and Statistics at the University of St. Andrews, Scotland. He is also director of the world-leading Centre for Research into Ecological and Environmental Modelling (CREEM), an inter-disciplinary research group at the interface between ecology and statistics. Two relevant major focuses of Len’s research are statistical methods for population trend estimation (which has been working on since his PhD, at University of British Colombia, Canada, from 1993) and inferences from passive acoustic monitoring of cetaceans (which has been a major topic of research since 2007). One component of the latter has been his involvement in the design and analysis of the SAMBAH survey, a multi-national passive acoustic survey designed to estimate density of harbour porpoise in the Baltic by deploying CPODs at more than 300 sampling locations over a 2 year period, and performing associated calibration experiments. Over the past 21 years, Len has co-authored 67 peer-reviewed papers, 3 books, and a further 57 other publications or technical reports. He has been a keynote speaker at several major international conferences, most recently the International Statistical Ecology Conference (2012, topic: “The future of statistical ecology”) and the European Cetacean Society Conference (2013, topic: “Interdisciplinary approaches in the study of marine mammals: ecology meets statistics”).
Appendix 2: Model details


Let \( W_t(s_i) \) denote a random variable for mean acoustic click counts at the \( i \)th spatial location in the \( t \)th year. Because some of the data were zero, we used \( Y_t(s_i) = \log(W_t(s_i) + 1) \) for analysis.

To account for uneven effort per site, we divided the spatial model into a spatially structured component and an independent component (often called the nugget effect by geostatisticians). Then the set \{\( Y_t(s_i) \)\} were treated as spatially autocorrelated in a spatial linear mixed model,

\[
[Y_t(s_i) \mid \mu_t, Z_t(s_i), \sigma_z^2, n_{t,i}] = N(\mu_t + Z_t(s_i), \sigma_z^2 / n_{t,i})
\]

(A.1)

Where \( n_{t,i} \) is the number of sampling days for each site for each year. The \( n_{t,i} \) account for uneven sampling, and this can be also be viewed as measurement or sampling error in a hierarchical model. Let the vector \( z_t \) denotes all of the spatial random effects, \( Z_t(s_i) \), for the \( t \)th year,

\[
[z_t \mid \sigma_z^2, \rho] = N(0, \sigma_z^2 R_t(\rho)),
\]

where we assumed that years were independent, but that the spatial stochastic process had the same autocorrelation model among years; that is,

\[
\text{cov} \left( z_{2011}, z_{2012}, z_{2013} \right) = \sigma_z^2 \begin{pmatrix}
R_{2011}(\rho) & 0 & 0 \\
0 & R_{2012}(\rho) & 0 \\
0 & 0 & R_{2013}(\rho)
\end{pmatrix}.
\]

For spatial autocorrelation, we used the exponential model,

\[
\text{corr}(Z_t(s), Z_u(v)) = \begin{cases} 
\exp(-3h / \rho) & \text{for } t = u, \\
0 & \text{for } t \neq u,
\end{cases}
\]

where \( h \) is Euclidean distance. That is, let \( s = (s_x, s_y) \) be the \( x \)- and \( y \)-coordinates of one point, and \( v = (v_x, v_y) \) be the \( x \)- and \( y \)-coordinates of another point, then

\[
h = \sqrt{(s_x - v_x)^2 + (s_y - v_y)^2}.
\]

For the spatial analysis, latitude and longitude coordinates were projected onto the plane using a Universal Transversal Mercator (UTM) projection with a user-defined central meridian. The central meridian was computed as the center of the vaquita refuge. This minimizes distortion from the projection, and UTM is a distance-preserving projection. After projection, the UTM coordinates were converted from meters to kilometers, and translated in space so that 0 on the \( x \)-coordinate corresponded with the western-most coordinate of the vaquita refuge, and 0 on the \( y \)-coordinate corresponded with the southern-most coordinate of the vaquita refuge.

To complete the model, we specified the following prior distributions,

\[
\begin{align*}
\mu_{2011} & \sim \text{UNIF}(-10,10) \\
\mu_{2012} & \sim \text{UNIF}(-10,10) \\
\mu_{2013} & \sim \text{UNIF}(-10,10) \\
\sigma_z & \sim \text{UNIF}(0,10)
\end{align*}
\]
\[ \sigma \sim \text{UNIF}(0,10) \]
\[ \rho \sim \text{UNIF}(0,500) \]

Because the data were modeled on the log-scale, these are flat and non-informative priors that encompassed any reasonable range of values for the parameters. The posterior distribution of the model is,

\[ [\sigma, \sigma_z, \rho, z, \mu | y]. \quad (A.2) \]

We used Markov chain Monte Carlo (MCMC) methods, using the software package WinBUGS, to obtain a sample from the posterior distribution (A.2). We used a burn-in of 10,000 iterations, and then used 1,000,000 further iterations. For computer storage reasons, we kept a single iteration out of each 100, yielding a sample of 10,000 from the posterior distribution.

We were interested in several summaries derived from the posterior distribution. Let

\[ \hat{S}^k_i(\mathbf{s}_i) = \exp[\hat{\mu}^k_i + \hat{Z}^k_i(\mathbf{s}_i)] - 1 \]

be a spatially smoothed prediction for the \( t \)th year, at the \( i \)th site, and for the \( k \)th MCMC sample. Notice that these predictions smooth over the noisy process with variance \( \sigma^2_z \) contained in the model specification at the data level, and that we are putting the predictions back on the original scale of the data. Then, we take as an indicator of overall abundance, among all \( n \) sites for each year, as

\[ \hat{B}^k_i = \frac{1}{n} \sum_{i=1}^{n} \hat{S}^k_i(\mathbf{s}_i). \]

Finally, we were interested in average rate of change, as a proportion, for the two time increments. We decided to use the geometric mean\(^2\),

\[ \hat{r}^k = \left( \frac{\hat{B}^k_{2012}}{\hat{B}^k_{2011}} \right) \left( \frac{\hat{B}^k_{2013}}{\hat{B}^k_{2012}} \right)^{1/2} = \left( \frac{\hat{B}^k_{2013}}{\hat{B}^k_{2011}} \right)^{1/2}, \]

and based on this, the posterior probability of a decreasing population can be computed from the mean of

\[ \hat{p}^k = I(\hat{r}^k < 1), \]

where \( I(.) \) is the indicator function. Posterior summaries including means, medians, and variances of \( \hat{S}^k_i(\mathbf{s}_i), \hat{B}^k_i, \hat{r}^k \), and \( \hat{p}^k \), were obtained from the MCMC samples.

**RESULTS**

Maps of \( \hat{S}^k_i(\mathbf{s}_i) \) for each year and location are given below, where we used the median from the MCMC sample. The sites in 2011 and 2013 with circles around them and an ‘x’ through the circle indicate that data were missing for those years, so these are spatially interpolated values. Because modeling occurred on the log-scale, these missing values in particular had a wider variance, which had a large effect on the mean value when taking

\(^2\)Note that \( \hat{r}^k \) is the parameter for proportional rate of change which is referred to using the symbol \( \lambda \) elsewhere in this Appendix and the body of the report.
exponents to get back on the original scale of the data. So, for presentation purposes, we used the median.

The posterior distribution of the annual proportional change, \( \hat{r}^k \), is given below,

The mean of the posterior distribution for \( \hat{r}^k \) was 0.825, and the median was 0.812, indicating about 19% per year decrease in clicks. The 95% credibility interval, based on the 2.5% and 97.5% quantiles, was 0.500 to 1.26. The probability \( \hat{r}^k \) was less than one, i.e., \( \hat{p}^k \), was 0.862.
ASSESSING THE MODEL AND MCMC

Our primary goal was to obtain a sample of $\hat{\rho}^k$ in order to project the current population estimate from 2010. To test for convergence in the MCMC chain, we used the Geweke test, found in the R coda package. The result was a $z$-value of 0.863, which is assumed to be a standard normal random variate under the assumption that the MCMC sample is from a stationary distribution. Our result indicates very little reason to be concerned that this particular MCMC chain had not converged. The MCMC trace is shown below.

The trace of $\rho$ is given below,

Note that values seem to be truncated by the prior, which has an upper bound of 500. We did a sensitivity analysis, and increased it to 1000. Part of the explanation requires the trace of $\sigma_\varepsilon$ as well, which is given below.
When $\rho$ is increased to 1000, then $\sigma_z$ becomes truncated by its upper bound of 10. This is a well-known phenomenon in spatial statistics, where the model explores a more linear form of the autocorrelation function by increasing both $\rho$ and $\sigma_z$. In fact, the correlation between them, in the MCMC sample, is near 0.86. However, very large values of $\rho$ and $\sigma_z$, when they occur together, have little effect on the autocorrelation within the spatial distances seen within the data set. We saw no change in our inferences by continuing to increase either $\rho$ or $\sigma_z$, because eventually one of them would become truncated at their upper bound. We left the upper bound for the prior of $\rho$ as 500 (km), as that allowed a lot of autocorrelation among sites, and was far beyond the maximum distance among plots in the vaquita refuge.

The trace of the mean parameters $\mu_{2011}$, $\mu_{2012}$, and $\mu_{2013}$ also wander throughout their whole prior distribution. This is shown as a trace of the MCMC sample for $\mu_{2011}$ in the following figure,

![Trace of $\mu_{2011}$](image)

This may seem strange at first, especially since even the raw data (on the log scale) do not range from -10 to 10. The explanation lies in the fact that spatially autocorrelated random variables, such as the $Z_i(s_i)$, can wander far from their mean of zero, so the whole set $\{Z_i(s_i); i = 1, \ldots, n\}$ may be positive or negative. To examine this effect, we just chose $Z_{2011}^k(s_i)$ from the MCMC chain, and its correlation with $\mu_{2011}^k$ was -0.988. Thus, the MCMC sampler was behaving as expected.

The trace of $\sigma$ showed little irregularity, and is given below.

![Trace of $\sigma$](image)
OTHER SPATIAL AND TEMPORAL MODELING CONSIDERATIONS

Table 3 shows the raw data used for spatial modeling. We tried several spatial models, including embedding the spatial linear model into a generalized linear model (called model-based geostatistics by Diggle et al.), where the untransformed data, conditional on the mean, followed a Poisson or negative binomial distribution. However, estimation of site mean values, and even means over sites, was very unstable resulting in average click rates per year, such as $\hat{B}_k^t$, that were often in the thousands.

We also considered a spatial model where the spatial random effects were constant across years, so that the conditional mean in (A.1) was $\mu_t + Z(s_t)$ rather than $\mu_t + Z(s_t)$. This resulted in much steeper rates of decline, with a mean $\hat{r}_k$ of nearer 0.7 rather than 0.8. The reason can be seen in Table 3, and in particular if we focus on site 34. If the random effects are held constant through the years, then the predicted values in 2011 will largely follow the pattern seen in 2012 and 2013. For 2012 and 2013, site 34 was one of the highest sites, so when that “surface” is shifted to 2011, the predicted values had average values that were nearer 900 to 1000, rather than around 300 seen in Table 3. We felt that it was a strong assumption to hold the spatial surface constant across years, so we rejected the use of that model. Although there are very few data to look at yearly trend (only 2 years for site 34) within site, the current model fits the general trend.
Table 3. Mean click rates per site for each year, along with sampling effort. Median values for $\hat{S}_i(s_t)$ are shown in bold red for missing C-PODs in those years.

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<th>Site</th>
<th>Mean Clicks 2011</th>
<th>Mean Clicks 2012</th>
<th>Mean Clicks 2013</th>
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<th>Sample Days 2012</th>
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Non-spatial Mixture Model

Rationale: This approach attempts to draw on the strength of the sampling design; Spatial autocorrelation is not modeled.

Basic assumptions:
1. CPOD locations are representative of a sampled area that we wish to make inference about.
2. The mean number of clicks-per-effort-day for a CPOD is linearly related to the amount of use in the area considered to be sampled by that CPOD. Thus clicks-per-effort-day is taken as an index of use-days in the area.

If all CPOD locations had equivalent sampling effort, we could simply take the mean “clicks per effort-day” across CPODs in year $t$ as a robust estimate of the use-index for that year. Inference would be based on comparing the means between years and assessing the probability that they are different (which would depend on the variances of the estimates).

However, data are missing for some CPOD locations in some years (call these missing “CPOD-years”), and precision of the overall mean detection rate could potentially be improved (thereby increasing the power to detect annual changes) by accounting for spatial heterogeneity in CPOD detection rates. Therefore, interpolating the value of the use-index for missing CPOD-years and improving precision in the annual estimates for the use-index are the analysis objectives.

Data
$n_{kt} =$ number of clicks recorded at location $k$, year $t$
$d_{kt} =$ number of effort-days at location $k$, year $t$
$K = 45 =$ total number of CPOD locations with effort in at least one year
The data are truncated in time, i.e., only using recorded clicks and effort-days between Julian dates 170 and 231 (inclusive).

Model
The non-spatial mixture model draws on the strength of the sampling design (repeat samples from a fixed semi-regular grid throughout the study area), emphasizing a design-based rather than model-based approach to inference. Predicted click levels (mean number of clicks per season, $n_{kt}$) at individual CPOD locations are not based on a spatial model. Rather, within a generalized linear mixed model framework, individual CPOD locations are assigned probabilistically to one of $V = 3$ groups based on the level of detections they received across multiple years of sampling.

Predictions for individual locations are given by estimated means for the groups to which CPOD locations are attributed, i.e.,

$$n_{kt} \sim \text{Negative Binomial} \left(p_{kt}, r_{\{k,t\}}\right),$$
where \( p \) and \( r \) are negative binomial parameters. Exploratory general linearized linear model (GAM) analysis suggested that the click-rate data were well described by a negative binomial error distribution (see GAM section below). The expectation for \( n_{kt} \) (which we denote \( \mu_{kt} \)) is a function of the expected mean number of clicks per day \( (\theta_{v[k,t]}) \) and sampling effort \( (d_{kt}) \). The former depends on the group membership for CPOD \( k \) and the year:

\[
\mu_{kt} = \theta_{v[k,t]}d_{kt}.
\]

For the negative binomial, the expectation \( \mu_{kt} = r_{v[k,t]}(1-p_{kt})/p_{kt} \). We placed priors on \( \theta_{v[k,t]} \) and \( r_{v[k,t]} \) (see below), so that in each MCMC iteration, the value for \( p_{kt} = r_{v[k,t]}/(r_{v[k,t]} + \mu_{kt}) \).

CPOD location \( k \) is probabilistically assigned to a use-intensity group \( v \) based on the data recorded at \( k \) across the years during which CPOD \( k \) was functioning. In OpenBUGS, this was done using the “categorical distribution” (multivariate generalization of the Bernoulli):

\[
v[k] \sim \text{cat}(s_{vk}),
\]

where \( s_{vk} \) is the vector of probabilities for \( k \) being in group \( v \), which come from a Dirichlet prior distribution:

\[
s_{vk} \sim \text{Dirichlet}(\alpha_v),
\]

where \( \alpha_v \) are the Dirichlet intensity parameters. Setting \( \alpha_1 = \alpha_2 = \alpha_3 = 1 \) makes this distribution fairly uninformative, providing the flexibility for \( s_{vk} \) to take on any values that sum to 1 (across \( v \) for each \( k \)).

The degree of certainty in assigning a CPOD location to a particular group depends on how correlated detections are through time; sites with consistently low or high levels of detections (or with more years of information, since there were some missing CPOD-years) are assigned to a group with greater confidence. Uncertainty in group assignment is propagated through to estimates of other parameters.

In short, the number of detections recorded across all CPODs are assumed to arise from a mixture of \( V \) negative binomial distributions in each year. Information across years is shared for the purpose of assigning each CPOD location to a particular group \( v \), but the means and variances for each \( v, t \) are independent. Predicted estimates for CPOD locations in years with missing data are based on the probability of belonging to group \( v \), and the conditional expected mean and variance for group \( v \) in year \( t \).

Inference is on the overall mean values for daily click rate \( (M_t) \), which are simply the means of the \( \theta_{v[k,t]} \) weighted by the number of CPODs belonging to each group \( v \) for each \( t \), i.e., \( M_t = \frac{1}{K} \sum_{k=1}^{K} \theta_{v[k,t]} \). The rate of change between 2011 and 2012 is \( M_2/M_1 \).

The rate of change between 2013 and 2012 is \( M_3/M_2 \). The mean annual rate of change, \( \lambda \), is the geometric mean of these two values. The probability that the population declined from 2011 to 2013 is the proportion of the Bayesian posterior distribution for \( \lambda \) that is less than 1. Inference about population change is based on posterior distribution summaries for these derived parameters.
Additional assumptions

In addition to the basic assumptions above, we note the following:

1. We used $V = 3$ groups based on visual inspection of the data, which indicates locations for which the mean number of clicks per effort day is consistently extremely low (just a few clicks/day), very high (clicks/day = hundreds to low thousands), or in-between (clicks per day = tens). Using fewer groups, such as $V = 1$ (single group, no mixture), ignores this information, potentially biasing estimates of $\mu_{k,t}$ for missing CPOD-years (and hence for the $M_t$). On the other hand, assuming many groups ($V > 3$) may result in over-fitting the data, reducing precision in the estimates of $\mu_{k,t}$ and thus increasing uncertainty in $M_t$. In practice, data generated by a mixture of many processes tend to be well approximated by mixture models with just a few groups.

2. Justification for this general approach relies on the assumption that there are fixed high-use and low-use areas through time, i.e., on average, locations with the highest click-rates in two years will also have the highest click rates in the third year. However, the assumption, as modeled, allows for some flexibility in how the implied spatial patterns of vaquitas vary through time, because the mean click-rate differences between groupings are estimated independently for each year. Thus, for example, the mean click rate for “medium use” CPODs could theoretically be much higher than “low use” CPODS in one year but only slightly higher in another year. Simple Spearman correlations suggest that it is indeed reasonable to assume that relative use across individual CPODs was similar through time ($r_{s2011,2012} = 0.77$; $r_{s2012,2013} = 0.93$; $r_{s2011,2013} = 0.83$). Similarly, high certainty in the assignment of most CPODs to a particular one of the $V$ groups (see below) provided additional support for this assumption.

3. In contrast with spatial models, we are not borrowing information from surrounding CPODs to estimate values for CPOD $k$. All CPOD locations are treated as independent sample locations. The expected value for CPOD $k,t$ depends on which group $k$ belongs to (which is informed by data in other years at $k$) and on the mean and variance parameters for the group (which are informed by other CPODs in the same group, but irrespective of their proximity to $k$).
MCMC specifications

An MCMC chain of length 1,000,000 was run. The first 500,000 samples were discarded. Every 100th sample from the chain was retained, so that the posterior distributions were to constructed from 10,000 samples.

The following prior distributions were used:

\( s_{vk} \sim \text{Dirichlet}(1, 1, 1) \)  # Probability of CPOD \( k \) belonging to group \( v \)

\( \log(\theta_{v[k],t}) \sim \text{Normal}(-10, \sigma^2=1000), \) for \( v = 1; \)

\[ \theta_{v[k],t} = \theta_{v-1[k],t} + \exp[\Delta \log(\theta_{v[k],t})], \] for \( v = 2, 3 \)

\( \Delta \log(\theta_{v[k],t}) \sim \text{Normal}(5, \sigma^2=1000) \) (left-truncated at zero to be positive)

\( r_{v[k],t} \sim \text{Categorical}(z^3), \) where \( z \) is a vector of probabilities for \( r \) = integers from 1 to 10;

\( z_r \sim \text{Dirichlet}(1) \) for all \( r \)

\[ p_{kt} = r_{v[k],t} / (r_{v[k],t} + \mu_{kt}) \]  # Negative binomial parameter

Results

Most CPODs were attributed to mixture group with high probability, though assignment was less clear (but still fairly confident) in a few cases (see examples in Figure 11).

\[ ^3 \text{In WinBUGS and OpenBUGS, the negative binomial } r \text{ parameter must be an integer } \geq 1. \]
Figure 11. Sample OpenBugs output. Posterior densities for assignment of individual CPODs to one of three mixture groups. CPODs 7 – 12 shown here for example. CPODs 7, 8, 9, 11 were assigned to group 2 with high certainty. Detector 12 was assigned to group 1 with fairly high certainty. CPOD 10 was assigned with the least certainty of all CPODs.

Figure 12 shows annual predictions of mean click rate (average number of clicks per day) for the 45 CPODs that functioned in at least one year. Values depend on the mixture group to which the CPOD is most commonly assigned. Assignment of CPODs to mixture groups was generally clear. Detectors receiving almost no clicks in any year were assigned to one group; detectors receiving on the order of tens of clicks per day were assigned to a different group; and detectors receiving an average of hundreds of clicks per day in at least one year tended to be assigned to the third group. This third group was the most variable; hence the expected clicks/day for CPODs in this group had the highest variance, as indicated by broader credible interval bars, but overall the pattern of residuals indicated reasonable fit of this model to the data.
Figure 12. A) Observed and expected values for “mean clicks per day” at each CPOD location that functioned in at least one year, 2011 to 2013. Solid black points are the observed values, with point size indicating the relative level of effort (large circles = more days of sampling). Open circles are the model-expected values (with 90% credible intervals) $\hat{\theta}_{v|\text{M}_1}$ for the three mixture groups (with most likely group indicated by different colors). Horizontal black line is the estimated overall mean for the year, $M_t$. Here, the y-axis only goes to 1000 (so that lower estimates may be visually resolved).
The posterior mean for $\bar{\lambda}$ was 0.81 with a 95% credible interval ranging from 0.57 to 1.13 (Figure 14). The probability that $\bar{\lambda}$ is less than 1 was 0.91.
Generalized Additive Models

Vaquita Trend Analyses with Generalized Additive Models (GAMs)

Introduction

Generalized Additive Models (GAMs) were developed to quickly evaluate and compare alternative models for estimating population change before implementing those models in Bayesian models. In the GAMs, year was treated as a categorical explanatory variable (2011, 2012 and 2013) and spatial variation was modeled as a two-dimensional thin-plate spline using the mgcv package in R (v. 3.0.1). It was assumed that the spatial distribution of vaquitas was the same across years and that, between years, relative densities changed proportionately among all sites. GAMs that estimated different spatial patterns for each year were generally not stable and are not reported here. The spatial distribution was modeled using all years, but inference on the rate of change in population size was based on the ratio of mean of predicted values in 2013 to the mean predicted values in 2011. To maintain a balanced geographic coverage for this comparison, spatial predictions were made using predict.gam on the grid of 45 C-POD stations for which data were available in at least one year. Unless noted otherwise, the GAM analyses were based on the core sampling period (between Julian days 170 and 231, inclusive) when at least 50% of C-POD stations were deployed in each year.

Three common statistical distributions (Poisson, negative binomial and Tweedie distributions) were fit to each dependent variable used, and the best fit was evaluated by visual appraisal of the QQ plots. The negative binomial provided the best fit to all the dependent variables explored here. Within mgcv, the binomial parameter \( \theta \) was specified as a range and that range was adjusted as necessary.
to ensure that best-fit value was not outside the range of potential values. When a mean of daily values was used as a dependent variable, the number of days was used as an offset to account for the unequal sample size.

Model Results
When total clicks per day were used as a dependent variable, none of the statistical models provided a good fit, but the negative binomial (Fig. 15) fit better than the Poisson or Tweedie distributions. This model (below) estimated a decline of 24.0% per year from 2011 to 2013. Due to the lack of fit between the data and the assumed distribution, inferences based on this model should not be trusted. Total clicks per day were not considered in any subsequent models.

Family: Negative Binomial(0.058)
Link function: log

Formula:
Clicks ~ as.factor(Year) + s(x, y, bs = "tp")

Parametric coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | 2.3490 | 0.1017 | 23.104 < 2e-16 *** |
| as.factor(Year)2012 | -0.1428 | 0.1266 | -1.128 0.259 |
| as.factor(Year)2013 | -0.5482 | 0.1326 | -4.135 3.55e-05 *** |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ‘ 1

Approximate significance of smooth terms:
edf df chi.sq p-value
s(x,y) 28.66 28.99 2567 <2e-16 ***

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ‘ 1

R-sq.(adj) = 0.193   Deviance explained = 39.5%
UBRE score = -0.51513  Scale est. = 1         n = 7269

Figure 15. Quantile-quantile plot showing how well the best statistical distribution (negative binomial) fit the distribution of total clicks per day. Ideally, all the points would fall on the line if the theoretical distribution fit the distribution of the data perfectly.
When mean clicks per day (averaged over all days for a given site and year) was used as a dependent variable, a negative binomial distribution provided a very good fit to the data. This model (below) explained 81% of the deviance in the data and estimated a decline of 27.2% per year from 2011 to 2013.

**Family:** Negative Binomial(1.011)
**Link function:** log

**Formula:**
Clicks ~ as.factor(Year) + s(Lat, Long, bs = "tp") + offset(log(Days))

**Parametric coefficients:**

| Parameter | Estimate | Std. Error | z value | Pr(>|z|) |
|-----------|----------|------------|---------|----------|
| (Intercept) | -1.2218 | 0.2017 | -6.057 | 1.38e-09 *** |
| as.factor(Year)2012 | -0.5075 | 0.2501 | -2.029 | 0.0424 * |
| as.factor(Year)2013 | -0.6358 | 0.2546 | -2.497 | 0.0125 * |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

**Approximate significance of smooth terms:**

edfRef.dfChi.sq p-value
s(Lat,Long) 26.24 28.38 488.6 <2e-16 ***

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

**R-sq.(adj) = 0.0484**  Deviance explained = 81.1%
**UBRE score = 0.74932**  Scale est. = 1  **n = 128**

---

Figure 16. Quantile-quantile plot showing how well the best statistical distribution (negative binomial) fit the distribution of mean clicks per day (averaged over all days for each station and year). Note that the negative binomial distribution provided a much better fit for mean clicks per day than for total clicks per day (Figure 15).

The previous analysis was limited to the core sampling period. The same analysis was repeated using the entire sampling period from the initial deployment of C-PODs each year just before the earliest start of the shrimp fishing season in all three years (i.e, until September 14, Julian day 254). The resulting model (below) gave a
lower estimate of the rate of decline (17.4% per year). By prior agreement of the expert panel, this longer sampling period was not used in subsequent analyses because the unequal spatial and temporal distribution of C-POD deployments would not provide robust estimates of the rate of decline.

**Family: Negative Binomial(0.893)**  
**Link function: log**

**Formula:**  
\text{Clicks} \sim \text{as.factor(Year)} + s(x, y, bs = "tp") + \text{offset(log(Days))}

**Parametric coefficients:**

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -1.2318 | 0.1935 | -6.365 | 1.96e-10 *** |
| as.factor(Year)2012 | -0.4050 | 0.2572 | -1.575 | 0.115 |
| as.factor(Year)2013 | -0.3825 | 0.2615 | -1.463 | 0.144 |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:

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Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

**R-sq.(adj) = 0.204 Deviance explained = 77.5%**

Some previous studies of relative porpoise abundance using C-PODs have been based on detection positive minutes, that is the number of minutes per day with at least one porpoise click. When mean detection positive minutes (DPM) per day (averaged over all days for a given site and year) was used as a dependent variable, a negative binomial distribution provided a reasonable fit to the data (Figure 17). This model (below) explained 86% of the deviance in the data and estimated a decline of 20.7% per year from 2011 to 2013, which is less than the rate of decline estimated using mean clicks per day (see Table 2 in Report body).

**Family: Negative Binomial(3.93)**  
**Link function: log**

**Formula:**  
\text{DPMs} \sim \text{as.factor(Year)} + s(x, y, bs = "tp") + \text{offset(log(Days))}

**Parametric coefficients:**

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -4.5919 | 0.3275 | -14.020 | <2e-16 *** |
| as.factor(Year)2012 | -0.5241 | 0.2320 | -2.259 | 0.0239 * |
| as.factor(Year)2013 | -0.4651 | 0.2395 | -1.942 | 0.0522 . |

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:

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Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

**R-sq.(adj) = 0.51 Deviance explained = 86.4%**
"UBRE score = 0.14129  Scale est. = 1  n = 128

> Predictions = exp(predict.gam(NBmeanDPMs, newdata=PredictSurface))
> ratio2013to2011 = mean(Predictions[PredictSurface$Year==2013])/mean(Predictions[PredictSurface$Year==2011])
> ratio2013to2011; 1-sqrt(ratio2013to2011)
[1] 0.6281017
[1] 0.2074713

Figure 17. Quantile-quantile plot showing how well the best statistical distribution (negative binomial) fit the distribution of detection positive minutes (averaged over all days for each station and year).

We also explored the potential of using detection positive half-hour periods as a measure of relative vaquita density, that is the number of half-hour periods per day with at least one porpoise click. Preliminary analyses during the workshop showed that the vast majority of porpoise detections lasted less than half an hour, so half-hour periods should be relatively independent of each other. When mean detection positive half-hours (DPHH) per day (averaged over all days for a given site and year) was used as a dependent variable, a negative binomial distribution provided a marginally good fit to the data (Figure 18). This model (below) explained 78% of the deviance in the data and estimated a decline of 19.1% per year from 2011 to 2013, which is less than the rate of decline estimated using mean clicks per day (see Table 2 in Report).

Family: Negative Binomial(99186)
Link function: log

Formula:
DPHHs ~ as.factor(Year) + s(x, y, bs = "tp") + offset(log(Days))

Parametric coefficients:

|                              | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------------------|----------|------------|---------|----------|
| (Intercept)                  | -5.2635  | 0.3407     | -15.449 | <2e-16   ***|
| as.factor(Year)2012          | -0.4830  | 0.2322     | -2.080  | 0.0375   * |
| as.factor(Year)2013          | -0.4244  | 0.2420     | -1.754  | 0.0795   . |
Figure 18. Quantile-quantile plot showing how well the best statistical distribution (negative binomial) fit the distribution of detection positive half-hours (averaged over all days for each station and year). Note that the negative binomial distribution did not fit detection positive half-hours as well as it fit detection positive minutes (Fig. 14).

A better fit was obtained using total DPHH per day instead of using the mean DPHH. The negative binomial distribution fit total DPHH (Figure 19) much better than total clicks (Figure 15). That total DPHH model result is given below. The resulting rate of population decline for this model (26.1% per year) is very similar to that for the mean clicks per day model (27.2%, see first model above).

Family: Negative Binomial(0.833)
Link function: log

Formula:
DPHHs ~ as.factor(Year) + s(x, y, bs = "tp")

Parametric coefficients:

|             | Estimate | Std. Error | z value | Pr(>|z|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | -1.79679 | 0.09183    | -19.567 | < 2e-16  *** |
| as.factor(Year)2012 | -0.43563 | 0.06011    | -7.247  | 4.26e-13 *** |
| as.factor(Year)2013 | -0.60411 | 0.06472    | -9.335  | < 2e-16  *** |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
edfRef.df Chi.sq  p-value
s(x,y) 27.85 28.84 2983  <2e-16 ***
Figure 19. Quantile-quantile plot showing how well the best statistical distribution (negative binomial) fit the daily total of detection positive half-hours.
Appendix 3: Further data description

There were two efforts that were useful to Panelists in interpreting the data and considering how to choose an appropriate model. Station numbers are given in Figure 20. The first helpful effort was a representation of clicks through time for each station and for each year (Figure 21). The second analysis showed the relation between the mean and variance for mean clicks/CPOD day (Figure 22).

Figure 20. Position of the sampling sites inside the Vaquita Refuge (upper map, numbered circles). Below are the results of moorings and acoustic detectors deployed in 2011, 2012, and 2013. C-PODs were not deployed at sites 17, 18, and 33 in 2013 (X’s). The CPOD at site 32 in 2011 was recovered June 25, 2013 and data were included in this analysis. Circles indicate sites where data are available, diamonds indicate all equipment lost at that site, and squares indicate sites where the mooring was recovered without the detector or the detector was recovered without any data.
Figure 21. Detection Positive Minutes (DPM’s represented by crosses) (2011-2013) for every available sampling station. Tide heights for San Felipe (closest town to vaquita distribution area) are shown in the top panel for June – September, except for 2012 where period is extended because data were available through November for sites 11 and 15 (detectors recovered on 2013). In the lower panel blue triangles indicate the first sampling day and red triangles the last sampling day. C-PODs were turned throughout this period.
Figure 22. Variance and mean of log-transformed data, i.e., \( \text{var}[\log(x_k+1)] \) and \( \text{mean}[\log(x_k+1)] \), where \( x_k \) is the mean number of clicks per day for an individual CPOD location in a particular year (128 unique values) using data from the core sampling period. Each point represents the mean and variance of 10 ordered values (e.g., left-most point is mean and variance of the 10 lowest \( x_k \) values; next point is mean and variance of 2\(^{nd}\) lowest to 11\(^{th}\) lowest \( x_k \), etc.). Moving window approach results in serial autocorrelation in the variance values, but overall the variance is relatively constant with respect to the mean on the log scale (apart from a few outliers), justifying use of the Gaussian spatial model (constant variance assumption) of the log-transformed data.