Using MPA Watch Data to Analyze Human Activities Along the California Coast

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About this report

This report was prepared for the California Department of Fish and Wildlife (CDFW) to inform the Marine Protected Area (MPA) Decadal Management Review (DMR). It is one of two projects at the Center for Community and Citizen Science aimed at supporting this important milestone for the MPA Network in California:

- Examining the Role of Community and Citizen Science in Marine Protected Area Implementation; and
- Using MPA Watch Data to Analyze Human Activities Along the California Coast (this report).

Each of these projects directly addresses goals of the Marine Life Protection Act and the four pillars of MPA Management: Research and Monitoring; Outreach and Education; Enforcement and Compliance; and Policy and Permitting. They also help to develop and expand a human dimensions research agenda for MPAs in California and beyond.

Acknowledgments

This project was supported by the Resources Legacy Fund, through a grant from the Once Through Cooling fund, administered by the California Ocean Protection Council. We received valuable guidance from both of those organizations, as well as the California Department of Fish and Wildlife. Two expert reviewers, Matt Williamson (Boise State University) and Ben Goldstein (UC Berkeley), were extremely generous with their time and expertise. We thank Mark Briggs for visual design and formatting of the report. Finally, the many different organizations that make MPA Watch possible have also been crucial to this project; we thank them for their time, energy, and feedback throughout the process.

Cover Photography
(Clockwise from left) Orange County Coastkeeper; Santa Barbara Channelkeeper; Orange County Coastkeeper

Design
Mark Briggs

Highlights

Information about human activities along the coast can help us understand human impacts on natural resources and the benefits people derive from marine protected areas (MPAs). In this project we examined human activities along the California coast from 2012 to 2020 using data from the MPA Watch community science network, gathered by more than 1,900 volunteer participants, and a handful of program staff.

Key messages and findings

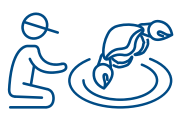
MPA Watch is gathering useful data at a statewide scale, and has successfully grown its network of volunteer monitoring programs over the last decade to include 12 local programs, 104 monitoring sites, and hundreds of volunteer surveyors each year (page 3).

Among the observations recorded by MPA Watch surveyors, **non-consumptive activities vastly outnumber consumptive activities**, both inside and outside of MPAs (Figure 4, page 5). This highlights the value of MPA Watch data for understanding human coastal use, underscores the importance of recreational activities in California's coastal economy, and reinforces the need to monitor and understand non-consumptive uses in and around MPAs.

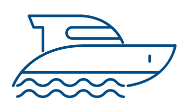
Our analysis confirms that **MPA Watch data can detect broad, statistically robust patterns** in human activities along the coast (page 6), including among recreational activities that relate to Goal 3 of the Marine Life Protection Act, but have not been the focus of other socioeconomic monitoring projects.

MPA Watch data can be used to detect statistically significant differences between activities inside and outside of MPAs (Table 1, page 6). Our analysis used occupancy modeling to investigate occurrence probabilities for seven categories of human activity. Our statistical results focus on an activity's likelihood of occurrence, rather than the total number of occurrences. From 2012 to 2020 at the statewide level:

Onshore fishing was **less likely** inside of MPAs.



Tidepooling was **more likely** inside of MPAs.



Recreational boating was **more likely** inside of MPAs.

Recommendations

- Continued and expanded monitoring could reveal statewide temporal trends that may be occurring, but are not yet statistically detectable with only nine years of data.
- MPA Watch can make improvements to its program without sacrificing the utility of past data through:
  - Consistent implementation of the surveyor ID system.
  - Updating protocols for recording potential violations.
- MPA managers can improve their ability to use MPA Watch data through:
  - Coordination between law enforcement data collection and MPA Watch.
  - Identifying specific questions about human uses to guide future analyses.
- There are many ways to improve and build upon the analysis presented here, including:
  - Investigating spatial patterns by leveraging data about covariates such as public access, and other site-specific attributes, and investigating seasonal within-year patterns in activities.
  - Developing models that examine the count of activities at a given site, in addition to this report's examination of presence/absence of activities.

Introduction

This report presents an analysis of human activities along the California coast from 2012 through 2020. Data for the analysis were collected by surveyors in a community science[1] monitoring network known as MPA Watch.

Goal of analysis

The primary goal of this project was to investigate human activities along the coast, looking for patterns, trends and shifts in consumptive and non-consumptive uses of marine ecosystems following implementation of MPAs. Of particular interest within this broad goal was:

1. Differences in activities between MPA and non-MPA sites; and
2. Patterns in activities that represent potential violations of MPA regulations.

Why does this matter?

Analysis of MPA Watch data contributes to a broader understanding of human impacts on marine ecosystems, and of the benefits that marine ecosystems provide to humans. Analysis of MPA Watch data can inform efforts toward goals 1, 2, and 4 of the Marine Life Protection Act (MLPA)[2], which guided the development of California's network of MPAs, by shedding light on human activities that could impact marine ecosystems. Goal 3 of the MLPA also calls out the role of MPAs in improving recreational, educational, and study opportunities in ecosystems subject to minimal human disturbance. Analysis of human activities inside and outside of MPAs can help us to understand progress toward that goal, as well as large-scale patterns in human recreation throughout the coast.

What is MPA Watch?[3]

MPA Watch is a network of programs that collect observations of human activities inside and outside of MPAs in California. Data are gathered by MPA Watch surveyors (mostly volunteers and a small number of paid staff) who travel to a predefined location and record observations on a data sheet that is later digitized in an online database. Most MPA Watch observations occur as a surveyor walks along the coast (beach or bluffs), though some programs also collect observations from a single vantage point, or by boat.

To date, 12 programs have been involved in the MPA Watch network. The observation protocol has been designed for consistency in data collection in which all programs use the same data sheet and manual,[4] and for flexibility of implementation due to significant variation in human and environmental geography along the coast.

[1] There are multiple terms for research and monitoring that involves people who do not self-identify as professional scientists (and are often volunteers). The MPA Watch network uses the term "community science," and so we will use that term throughout this report, except when discussing the broader field of practice, for which we use the term "community and citizen science." See more in a separate DMR report: "Examining the Role of Community and Citizen Science in Marine Protected Area Implementation."

[2] *Marine Life Protection Act.* 1999. Vol. Ch. 1015, Sec. 1. https://leginfo.legislature.ca.gov/faces/codes_displayText.xhtml?lawCode=FGC&division=3.&title=&part=&chapter=10.5.&article=

[3] See also the DMR report: "MPA Watch: Community Science for Stewardship of Ocean Resources"

[4] Data sheet, manual, and other program resources available at https://mpawatch.org/resources. See also the report submitted by the MPA Watch network for the DMR: "MPA Watch: Community Science for Stewardship of Ocean Resources"

Box 1. MPA Watch at a glance

Key terms and concepts

- *MPA Watch:* The statewide network of monitoring programs that contribute data using aligned methods and protocols.
- *MPA Watch program or "program" for short:* A local chapter of MPA Watch, run by one or more local organizations. Each program monitors a distinct set of sites.
- *Site:* An area targeted for data collection by MPA Watch (can be an MPA or a non-MPA reference site).
- *Non-MPA Site:* An area targeted for data collection that is not within an MPA. Because there is not a standard state-wide approach for identifying such sites, we use the term "non-MPA" rather than "control" or "reference" in this report.[5]
- *Transect:* Area covered by a single survey, conducted by an MPA Watch volunteer. On land, a transect is usually designed to take an hour or less on foot. Many sites contain multiple transects.
- *MPA Watch surveyor or "surveyor" for short:* A person who has received training from an MPA Watch program, and has approval to travel to collect and contribute data for the network.

Key facts and figures (2012–2020)

- Number of chapters: 12
- Number of survey sites: 104 (44 MPA sites, and 60 non-MPA sites)
- Number of individual volunteers since 2012 (estimated): 1918[6]
- Surveys conducted 2012 through 2020: 31,702
- Activities observed 2012 through 2020: > 1.2 million

While there are multiple ways to monitor human activity along the coast (e.g., lifeguard beach counts, parking lot counts, phone surveys), MPA Watch has a significant advantage in providing monitoring that is detailed (surveyors identify specific activities, not just counts of people), repeated (surveys are collected at the same site at many points of time, over multiple years), and standard (surveys across the state follow the same format)[7].

The MPA Watch network grew rapidly between 2011 and 2015, both in its geographic coverage (Figure 1) and in the number of people participating as surveyors (Figure 2; see also Appendix A), which includes breakdowns by site and bioregion). Some growth in coverage continued through 2020, even while there was a slight drop-off in overall participation. MPA Watch surveyors collect data throughout the year, with slightly more activity in summer months (Figure 3). Surveyor activity dropped briefly in March–June 2020, coincident with California's COVID-19 shelter-in-place orders, but quickly returned to pre-2020 levels (Figure 3).

[5] For example, some non-MPA sites are chosen for similar habitat (e.g., rocky intertidal, kelp forest), while others may be chosen to examine potential "edge effects" on either side of an MPA.

[6] This underestimate is based on data from the MPA Watch database. Programs have different data entry practices: in some cases program staff enter data for their surveyors and in others, individuals enter their own data. This leads to undercounting. As detailed in the separate DMR submission from the MPA Watch network, more than 4,000 surveyors have participated since the start of the program. This number was generated after our own analysis was completed and cannot be broken down by year.

[7] We also note that MPA monitoring in California has included in-depth, multi-method investigations of consumptive uses, both commercial and recreational, including the long-term monitoring project focused on commercial fishing and commercial passenger fishing vessels (CPFVs).

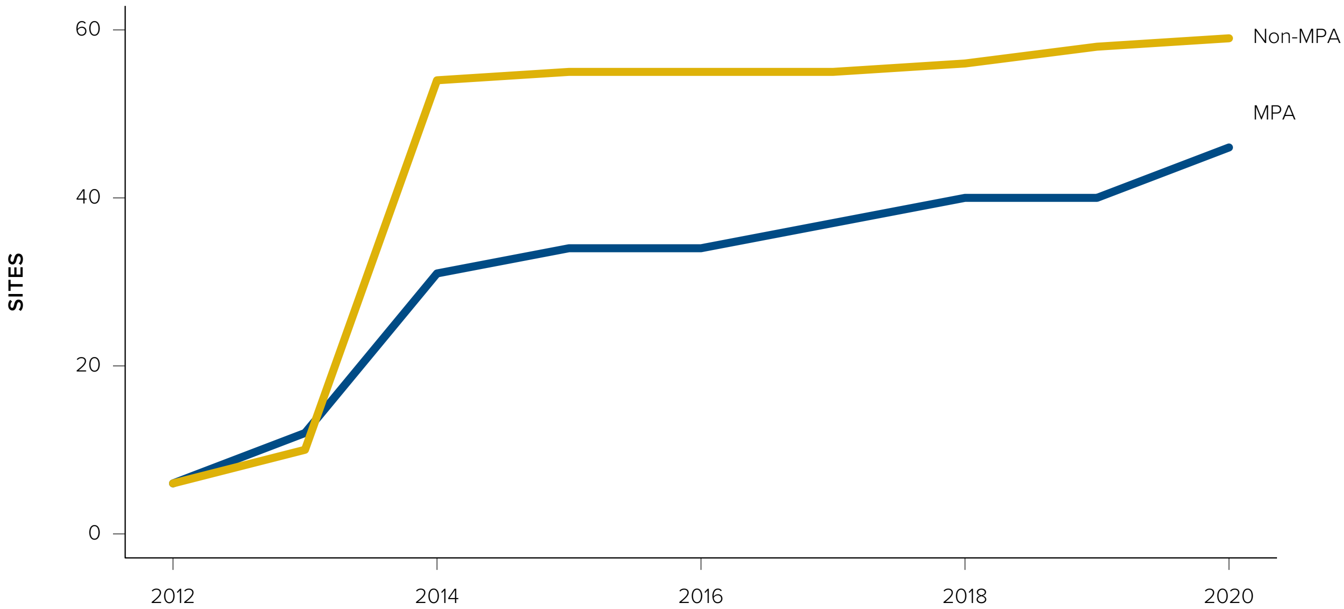


Figure 1. Cumulative sites in the MPA Watch Network over time. Count is based on the "first survey date" of each site (i.e., data do not reflect possible later elimination of sites from the sampling regime). Note the sharp increase in non-MPA sites around 2013, when the Beach Watch program joined the network. Beach Watch began operating in 1993, before MPA implementation, and many of its sites do not happen to be located in MPAs.

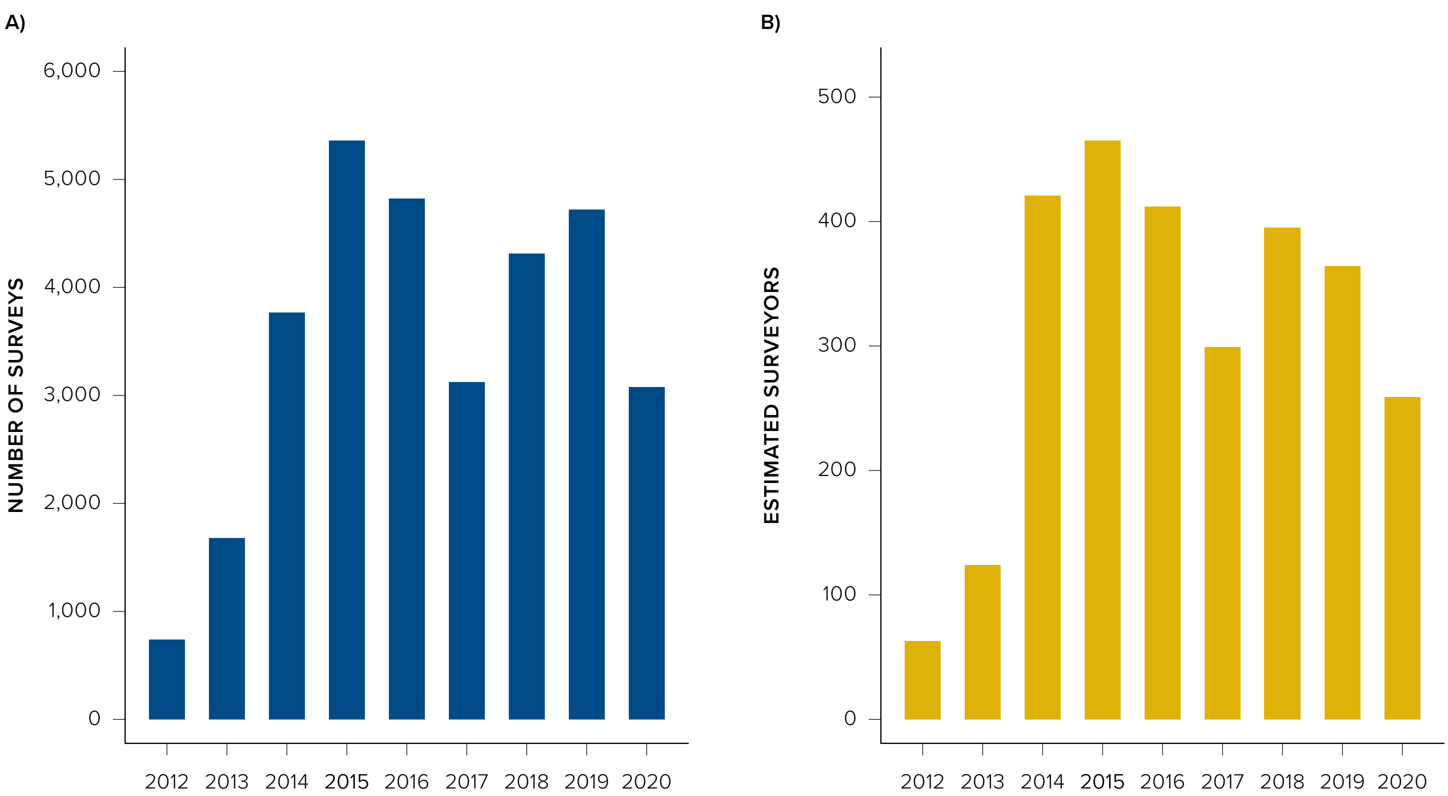


Figure 2. Number of surveys (Panel A) and estimated surveyors (Panel B) per year in the MPA Watch network. Undercounting of surveyors stems from cases of data entry by program staff, rather than surveyors.

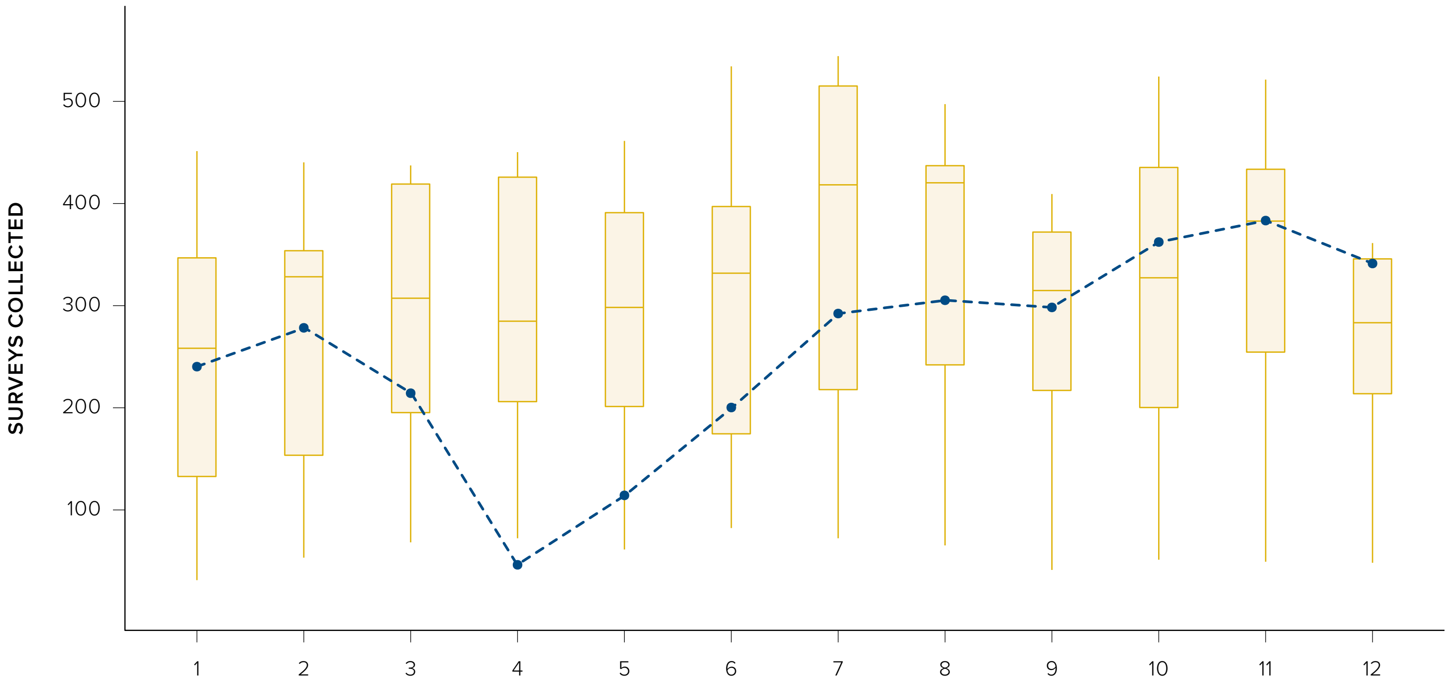


Figure 3. Surveys conducted by month across all MPA Watch sites. Boxplots show survey collection from 2012–2019; blue points show survey collection in 2020. Note weak seasonality in survey collection, with a slightly greater number of surveys collected in summer on average, and short-term decline in survey activity during the initial COVID shut-down.

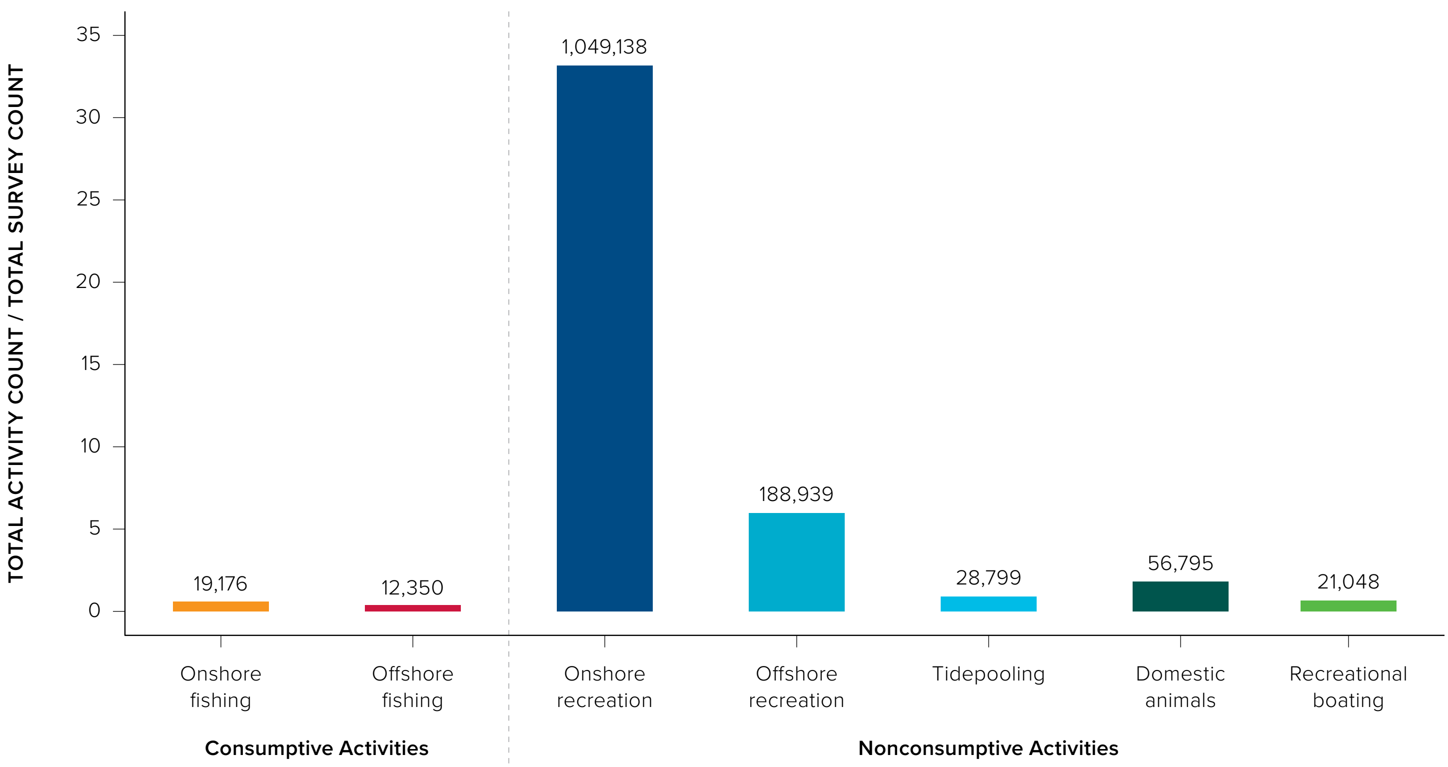


Figure 4. Counts of activities observed by MPA Watch surveyors from 2012 through 2020 in the seven categories of activity created for our analysis. Consumptive activities are onshore and offshore fishing; nonconsumptive activities include all remaining activity categories.

What does MPA Watch monitor?

The data sheet used by MPA Watch surveyors includes 66 types of human activity. For this analysis, we have grouped many of those activities into seven broad categories. We used two categories of consumptive activity: onshore fishing, and offshore fishing. We used five categories of non-consumptive activity: onshore recreation; domestic animals; tidepooling; offshore recreation; and recreational boating.[8] **The vast majority of activities observed by MPA Watch are in the onshore recreation category, with a very small percentage associated with consumptive activity** (Figure 4).

Statistical Modeling of MPA Watch Data

As with many community and citizen science programs, the data from MPA Watch are rich, but can be challenging to evaluate at a statewide level over the entire timeframe of data collection. This stems from the program's gradual growth in spatial coverage over time from south to north, and the fact that sampling by surveyors is voluntary and can be sporadic, with some sites sampled more consistently than others. We used a method called "Occupancy Modeling" to account for this uneven sampling in order to answer key questions about coastal use in a statistically robust way. Occupancy modeling addresses the "yes-no" question of *whether or not* an activity occurred, either statewide or at a given site or in a given year. Therefore our results do not directly address the question of *how many times* an activity occurred in a given year. For more details on the occupancy model, see Appendix B.

Can we detect patterns in human activities using MPA Watch data?

Yes. A key insight from this first effort to statistically model MPA Watch data is that the dataset is a rich resource, with the potential to address important questions about consumptive and non-consumptive uses of coastal natural resources. Importantly, we can also analyze differences between activities occurring inside and outside of MPAs.

Are activity patterns different inside of MPAs?

Yes, for some activities (for example, see results for Onshore Fishing, Figure 5A). A key question for this project was whether there are statistically significant differences between human activities taking place inside of, and outside of, MPAs. As shown in Table 1, three of our activity categories – Onshore Fishing; Tidepooling; and Recreational Boating – showed a statistically significant MPA effect. This means that there was a higher (or lower) probability that at least one person was engaging in that activity in an average year inside an MPA as opposed to outside an MPA. The remaining categories did not show a significant link between MPA status and activity.

Category	MPA Effect*
Onshore Fishing	**Less** likely inside MPAs
Tidepooling	**More** likely inside MPAs
Recreational Boating[9]	**More** likely inside MPAs

Table 1. Modeled effect of MPAs on human activities.

* No significant effect for Offshore Fishing, Onshore Recreation, Offshore Recreation, or Domestic Animals

[8] See appendix A to review the MPA Watch data sheet, and an account of which activities are lumped into the seven categories. Note that we did not include all activity types, because some contain extremely small numbers of observations, and cannot be lumped easily into larger categories.
[9] This category includes: Paddle Operated Boat; Kayak; Power boat; Sail boat; Jet ski; Dive boat; Whale Watching Boat.

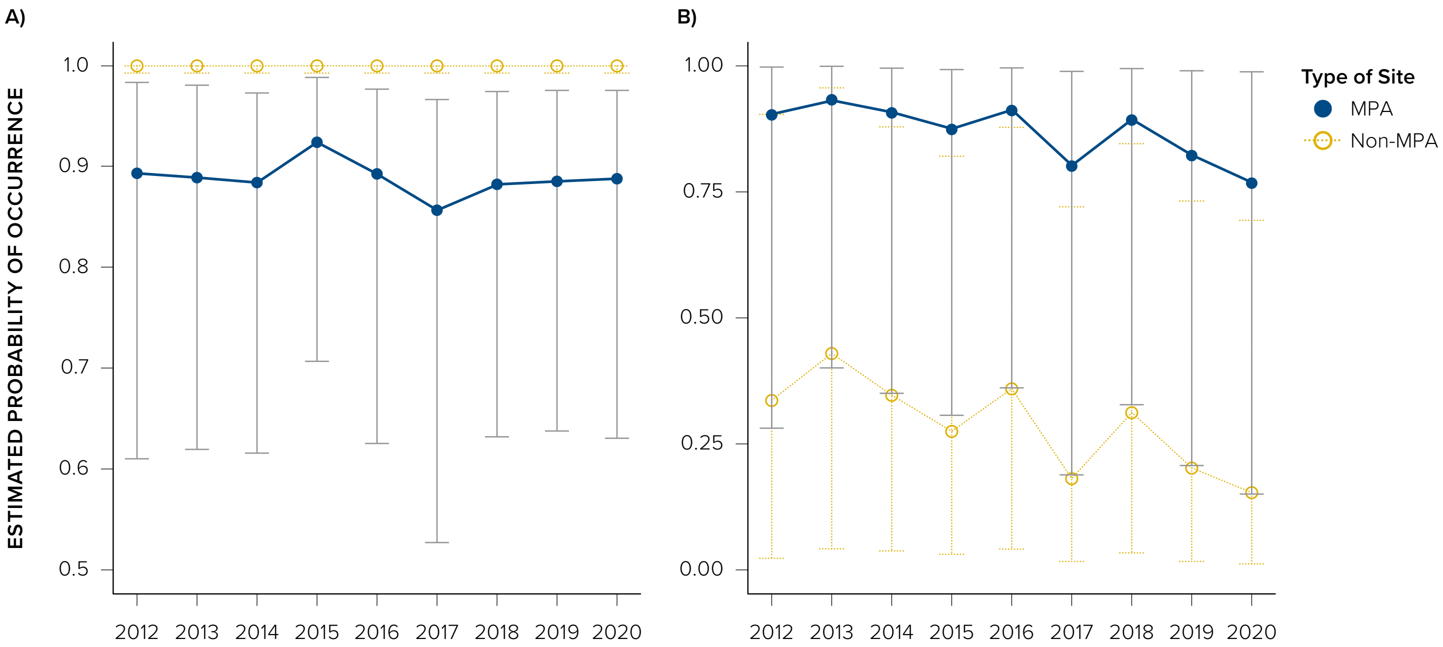


Figure 5. The statistical models show significantly **lower occurrence of onshore fishing in MPA sites** versus non-MPA sites, and little variation from year to year (Panel A). The model shows a **potential trend toward declining tidepooling** in later years, though this pattern is not yet statistically significant (Panel B). (Note that the probability in Panel A ranges from 0.5 to 1, and from 0 to 1 in Panel B.)

Figure 6. Occupancy model output showing site-level probability of tidepooling occurrence in the South Coast bioregion for MPA (filled circles) and non-MPA (outlined circles) sites. Lighter greens indicate lower probabilities of the activity occurring in an average year, and darker blues indicate higher probabilities.

Do activity patterns change over time?

Yes. There is some variation from year to year in the probability of activities occurring at the statewide level for 2012–2020, but no clear trends. Some activities show the possible beginnings of trends: for example, tidepooling seems to be gradually declining over the past nine years (Figure 5B). However, the existing time series is not long enough to disentangle trends from typical yearly variation.

Do different sites experience more or less human activity?

Yes. In our analysis, activities vary across different sites based on unmodeled attributes beyond MPA or non-MPA status. Some activities, like onshore recreation, occur consistently across all sites. Other activities, such as tidepooling, are more likely to occur at some sites than others (Figure 6) The model does not tell us anything about the numbers of people at different sites, but just the probability of at least one person tidepooling in an average year at that site. The variation in site-level effects uncovered in this phase of analysis highlights a promising area for further work to understand how different specific site attributes beyond MPA status influence activity patterns. These attributes could include factors like parking, site amenities, and natural attributes of the site like coastline type (e.g. beach versus bluff). Future models can explicitly include and test for the impacts of these factors.

Does population density explain human activity patterns across sites?

Not in this analysis. California's coast encompasses a wide range of population densities, from dense metropolitan areas to less populated rural sites, and these differences in population may impact coastal activity. We tested the influence of nearby population density (from U.S. Census data, see Appendix B for more details) on activity occurrence at each site. However, model results showed that **this measure of population density had no influence on the probability of an activity occurring**; this means that all recorded activities were equally likely to occur in an average year along all of California's MPAs, regardless of population density differences. Future work could also test different measures of population density to assess effects on human activity occurrence, in addition to testing the influence of additional site-specific attributes.

What are the patterns of "potential violations" in MPA sites?

In this project, we assessed patterns of *potential* violations of MPA regulations. MPA Watch surveyors do not directly report potential violations. Instead MPA Watch used lists of prohibited activities at each MPA site to retroactively identify observations that constitute a potential violation, based on those site-specific regulations. This method may overcount violations due to challenges in differentiating between permitted and prohibited activities that are visually similar (e.g., certain types of onshore fishing may be permitted, but they may resemble prohibited types of onshore fishing). Furthermore, the overcounting issue is likely uneven across sites: data for so-called "no-take" MPAs may be much more accurate than for those MPAs that allow various kinds of consumptive activities.

At most sites, our model estimates a high probability of at least one potential violation occurring in an average year.

It is important to remember that a high probability of occurrence does not mean that potential violations occur in large numbers; rather, it means that most sites have at least one potential violation in an average year. The actual number of violations at a given site may still be quite low. Activity frequency – or the total number of potential violations in a given year, at a given site – is not addressed by the occupancy modeling approach.

To illustrate, drawing on raw data from MPA Watch: there are 2,925 surveys with at least one possible violation, amounting to around 13 percent of all surveys conducted in MPAs from 2012 through 2020. Though year-to-year variation was not statistically significant, the raw data suggest a decreasing trend (Figure 7). More years of data and a more consistent method of identifying potential violations would help to definitively answer whether there is a decrease. The model indicated that it is 96% likely that sites had at least one violation in an average year, though a few sites had significantly lower probabilities: Sea Lion Cove; Kashtayit; and Dana Point.

We urge caution in interpreting model results for potential violations, but nevertheless report them here. We believe that, with some adjustments and coordination with CDFW, there is strong potential for MPA Watch to generate useful data about potential violations at a scale that complements the data gathered by law enforcement.

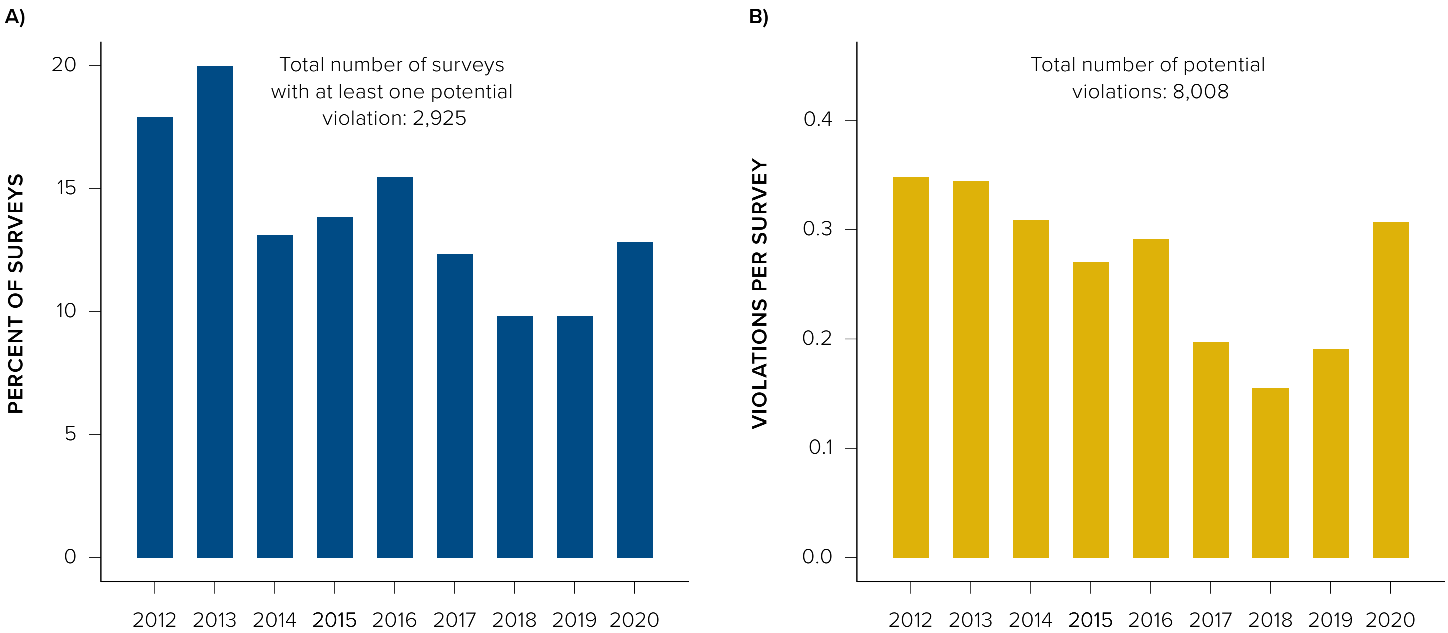


Figure 7. Panel A: Annual percentage of surveys conducted at MPA sites with at least one potential violation observed, from 2012 through 2020 (these are the data used in the model). Panel B: Number of potential violations per survey from 2012 through 2020.

Challenges and Recommendations

This project provides the first formal statistical analysis of MPA Watch data. We find that MPA Watch is generating a valuable dataset that can be used to robustly assess human activities along California's coast, both within and beyond MPAs. This analysis uncovered particular challenges in navigating the rich but complex nature of community science data, and suggests ways to build the contributions of MPA Watch to MPA and coastal management in California, through further analysis.

Challenges

Modeling limitations

This round of modeling simplified MPA Watch data to focus on the presence or absence of activities at MPA and non-MPA sites, and to examine patterns at the annual, statewide scale. Richer insights might be found by addressing activity counts at finer spatial and temporal scales, instead of presence or absence, although this will come with its own statistical challenges.

Relatively short time series

Our analysis did not reveal robust time trends in human activities from 2012–2020 at the statewide level. It is possible that some trends are underway, but that nine years is too short a timeframe for long-term change to be distinct from year-to-year variation.

Analyzing potential violations

As described above, the potential violations data used for this analysis have some flaws that could be addressed through a statewide protocol for direct observations (rather than retroactively processing the data, as was done for this analysis).

Recommendations

For future analyses

There is strong potential to gain more insights at finer spatial scales, and for specific activities of interest (as opposed to large groupings of diverse activities such as "onshore recreation"). We recommend that future modeling efforts experiment with:

- Testing the impact of site-specific attributes on activities;
- Modeling activity counts, rather than presence or absence;
- Studying within-year patterns of use; and
- Repeating analysis as the time series extends.

For the MPA Watch network

MPA Watch can make improvements to its program without sacrificing the utility of past data through:

- Consistently applying the existing surveyor unique ID, to help account for differences between surveyors.
- Updating protocols for recording potential violations, in collaboration with CDFW.

We also note two other more significant potential changes, which likely would require more data analysis and strategic planning before moving forward:

- We recommend that program managers and state partners develop a strategy and experimental design framework for designating future reference (non-MPA) sites.
- Survey effort could be balanced more evenly across sites and times of year. This likely cannot be done on a statewide basis, given the realities of travel times and distinct local programs in the network. But individual programs could develop incentives and targets to address local imbalances.

For MPA management

Sustain and expand the MPA Watch network. With continued support by the State and other funders, the value of MPA Watch data will grow over time. Continued monitoring could reveal statewide temporal trends that may be occurring, but are not yet detectable with only nine years of data. This could be enhanced still further if MPA Watch received support to expand monitoring to more MPA sites.

Leverage MPA Watch as part of a broader strategy for human dimensions research and monitoring. To help focus further analyses, MPA managers should identify specific questions (e.g., about specific activities, covariates, and/or focal areas) that fit into a broader human dimensions research agenda for MPAs, which has been called out as an important knowledge gap by the California Ocean Protection Council's Science Advisory Team.[10] We note also the MPA Watch network represents significant statewide capacity that could be leveraged for other data collection activities focused on human dimensions (e.g., on-site surveys of MPA users).

Align approaches to monitoring of potential violations. There is an opportunity to coordinate and develop shared expectations between MPA Watch and CDFW, and improve the role of MPA Watch data in enforcement and compliance.

[10] Hall-Arber, M., Murray, S., Aylesworth, L., Carr, M., Field, J., Grorud-Colvert, K., Martone, R., Nickols, K., Saarman, E., Wertz, S. Scientific Guidance for California's MPA Decadal Reviews: A Report by the Ocean Protection Council Science Advisory Team Working Group and California Ocean Science Trust, June 2021. https://www.oceansciencetrust.org/wp-content/uploads/2021/06/Evaluating-California%E2%80%99s-Marine-Protected-Area-Network-2021.pdf

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Appendix A: Further details on the MPA Watch dataset

This appendix contains the following additional details regarding the MPA Watch network and its associated dataset:

MPA Watch core data sheet 2

This is the sheet used by volunteer surveyors in all programs throughout the state

Guide to the seven categories of human activities 3

The MPA Watch data sheet includes many different categories of activities, which we have grouped into broader activity categories in our summary figures and model results. Here we list which activities were grouped into larger categories for analysis.

Adjusted counts of activities over time 5

Counts of all activities from all categories, broken out by year and divided by the number of surveys per year (because sampling effort varied each year).

Number of surveys at each site in each year 6

This table shows a breakdown of how many surveys were conducted at each site in each year

Breakdown of counts within activity categories 11

These pie charts summarize which of the specific activity categories made up the larger categories shown in the main report, and their relative proportion within those larger categories.

Data summaries by bioregion 14

We show the growth of the program by bioregion, including the counts of surveys over time in different parts of the State.

Occurrence probability for each site by bioregion 17

We give model results showing predicted site occupancy for each bioregion and activity.

MPA Watch core data sheet

Name(s):		Date: ___/___/______	Transect ID:
Start Time:	End Time:	Clouds: clear (0%)/ partly cloudy (1-50%)/ cloudy (>50%cover)	Precipitation: yes / no
Air Temperature: cold / cool / mild / warm / hot		Wind: calm / breezy / windy	Tide Level: low / med / high
Visibility: perfect / limited / shore only		Beach Status: open / posted / closed / unknown	

On-Shore Activities	Rocky	Sandy
Recreation (walking, resting, playing, etc. NOT tidepooling)		
Wildlife Watching		
Domestic animals on-leash		
Domestic animals off-leash		
Driving on the Beach		
Tide-pooling (not collecting)		
Hand collection of biota		
Shore-based hook and line fishing		
Shore-based trap fishing		
Shore-based net fishing		
Shore-based spear fishing		

Off-Shore Activities (Non-Boating)	
Offshore Recreation (e.g., swimming, bodysurfing)	
Board Sports (e.g., boogie boarding, surfing)	
Stand-Up Paddle Boarding (alternatively can tally in paddle operated boat below)	
Non-Consumptive SCUBA and snorkeling	
Spear Fishing (free diving or SCUBA)	
Other Consumptive Diving (e.g., nets, poles, traps)	

Boating	Recreational		Commercial		Unknown	
	Inactive	Active	Inactive	Active	Inactive	Active
Boat Fishing - Traps						
Boat Fishing - Line						
Boat Fishing - Nets						
Boat Fishing - Dive						
Boat Fishing - Spear						
Boat Kelp Harvesting						
Unknown Fishing Boat						
Paddle Operated Boat (can separately tally stand-up paddle boarding above under board sports)						
Dive Boat (stationary – flag up)						
Whale Watching Boat						
Work Boat (e.g., life-guard, DFW, research, coast guard)						
Commercial Passenger Fishing Vessel (5+ people)						
Other Boating (e.g., powerboat, sail boat, jet ski)						

Comments

Did you observe: ☐ scientific research; ☐ education; ☐ beach closure; ☐ large gatherings (e.g., beach cleanup); ☐ enforcement activity

Describe below and provide counts of individuals involved where possible, and whether it took place on rocky or sandy or sandy substrate.

Did you report a violation: ☐ yes ☐ no If yes, how many violations did you report ________

Who did you report the violation to (mark all that apply): ☐ DFW ☐ State Parks ☐ other entity (e.g., lifeguard, harbor patrol)

Which method did you use to report your violation (mark all that apply): ☐ phone call ☐ text ☐ mobile app ☐ website ☐ email ☐ in person

Guide to the seven categories of human activity used in our analysis

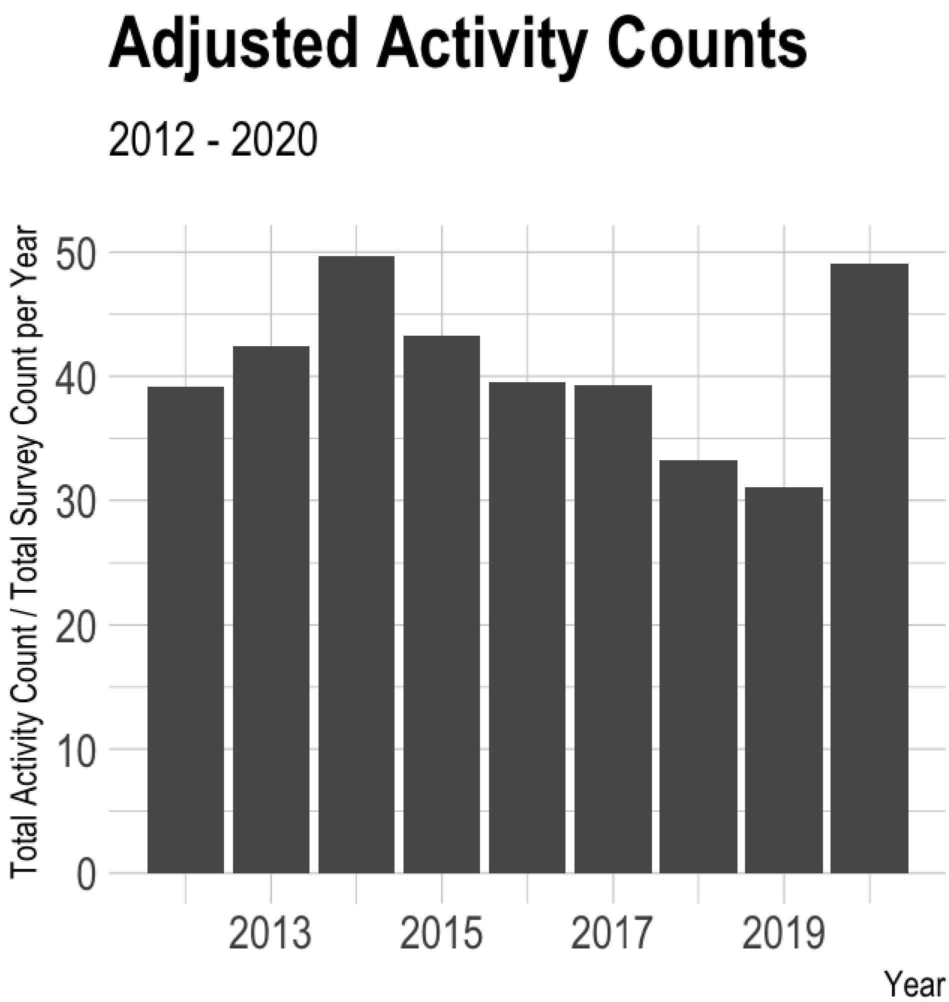
To facilitate data modeling and interpretation, we grouped MPA Watch Core Tally Sheet activities into larger activity categories. Certain activities on the MPA Watch Core Tally Sheet were excluded from analysis on the basis of very low occurrence over 10 years (e.g. Kelp Harvesting, Driving). Activities with a * are on the Tally Sheet, but as presence checkboxes, not counts. Activities with a ^ are present in a combined category on the Tally Sheet, and are differentiated here.

1. Onshore recreation
    a. Shore-based recreation (sandy) (NOT tidepooling)
    b. Shore-based recreation (rocky) (NOT tidepooling)
2. Domestic animals
    a. Domestic animals on-leash (sandy)
    b. Domestic animals on-leash (rocky)
    c. Domestic animals off-leash (sandy)
    d. Domestic animals off-leash (rocky)
3. Tidepooling
    a. Tidepooling
4. Onshore fishing
    a. Shore-based hook fishing (sandy)
    b. Shore-based hook fishing (rocky)
    c. Shore-based trap fishing (sandy)
    d. Shore-based trap fishing (rocky)
    e. Shore-based net fishing (sandy)
    f. Shore-based net fishing (rocky)
    g. Shore-based spear fishing (sandy)
    h. Shore-based spear fishing (rocky)
5. Offshore recreation
    a. Offshore recreation
    b. Board sports
    c. Surfing/boogie boarding ^
    d. Kitesurfing/windsurfing ^
    e. Stand-up paddle boarding (alternatively can tally in paddle operated boat)
    f. Non-consumptive scuba/snorkeling
6. Offshore fishing
    a. Boat fishing, traps, recreational (inactive)
    b. Boat fishing, traps, recreational (active)
    c. Boat fishing, traps, commercial (inactive)
    d. Boat fishing, traps, commercial (active)
    e. Boat fishing, traps, unknown (inactive)
    f. Boat fishing, traps, unknown (active)
    g. Boat fishing, line, recreational (inactive)
    h. Boat fishing, line, recreational (active)

   i. Boat fishing, line, commercial (inactive)
   j. Boat fishing, line, commercial (active)
   k. Boat fishing, line, unknown (inactive)
   l. Boat fishing, line, unknown (active)
   m. Boat fishing, nets, recreational (inactive)
   n. Boat fishing, nets, recreational (active)
   o. Boat fishing, nets, commercial (inactive)
   p. Boat fishing, nets, commercial (active)
   q. Boat fishing, nets, unknown (inactive)
   r. Boat fishing, nets, unknown (active)
   s. Boat fishing, dive, recreational (inactive)
   t. Boat fishing, dive, recreational (active)
   u. Boat fishing, dive, commercial (inactive)
   v. Boat fishing, dive, commercial (active)
   w. Boat fishing, dive, unknown (inactive)
   x. Boat fishing, dive, unknown (active)
   y. Boat fishing, spear, recreational (inactive)
   z. Boat fishing, spear, recreational (active)
   aa. Boat fishing, spear, commercial (inactive)
   bb. Boat fishing, spear, commercial (active)
   cc. Boat fishing, spear, unknown (inactive)
   dd. Boat fishing, spear, unknown (active)
7. Recreational boating
   a. Paddle Operated Boat
   b. Kayak
   c. Power boat^
   d. Sail boat^
   e. Jet ski^
   f. Dive boat
   g. Whale Watching Boat
8. Excluded activities from MPA Watch Core Tally Sheet
   a. Wildlife watching (sandy)
   b. Wildlife watching (rocky)
   c. Driving on the Beach
   d. Hand collection of biota (sandy)
   e. Hand collection of biota (rocky)
   f. Spear fishing (free diving or SCUBA)
   g. Other consumptive diving
   h. Kelp harvest (commercial, active)
   i. Kelp harvest (commercial, inactive)
   j. Kelp harvest (unknown, active)
   k. Kelp harvest (unknown, inactive)
   l. Work boat
   m. Commercial passenger fishing vessel
   n. Other boating
   o. Onshore enforcement*^
   p. Boat-based enforcement*^
   q. Onshore border patrol*^

Adjusted counts of activities over time

Typical numbers of people observed using coastal areas ranged from 30-50 per survey. The increase until 2014 and subsequent decline until 2019 could be due to the expansion of the MPA Watch network first in the south, with greater numbers of people using beaches and other areas, and then into more northern sites with fewer numbers of people engaging in the activities. This uneven distribution of sites over time is one reason for using the statistical models detailed in Appendix B, which account for such biases. The peak in 2020 could be due to the COVID-19 pandemic causing more people to choose to recreate outside, but further study as the pandemic evolves over time will allow a more careful analysis.



Number of surveys conducted at each site

Table A1: All sites, ordered North to South, and the number of surveys in each year. Note that these are the surveys used in the occupancy model; there may be more surveys in the larger dataset.

Site Name	2012	2013	2014	2015	2016	2017	2018	2019	2020
Pyramid Point SMCA	0	0	0	0	0	0	27	12	81
False Klamath Rock Special Closure	0	0	0	0	0	0	79	66	13
Samoa SMCA	0	0	0	0	0	0	0	0	4
CONTROL Manila Dunes	0	0	0	0	0	0	1	0	4
Sea Lion Gulch SMR	0	0	0	0	0	1	0	0	0
MacKerricher SMCA	0	0	0	0	0	0	0	0	13
Point Cabrillo SMR	0	0	0	0	0	0	0	0	4
Russian Gulch SMCA	0	0	0	0	0	0	0	0	4
CONTROL Big River Estuary	0	0	0	0	0	0	0	0	4
Big River Estuary SMCA	0	0	0	0	0	0	0	0	4
Van Damme SMCA	0	0	0	0	0	0	0	0	4
CONTROL South Manchester Beach	0	0	2	13	12	25	22	20	7
Sea Lion Cove SMCA	0	0	0	12	12	17	26	21	16
Del Mar Landing SMR	0	0	0	13	13	16	25	23	9
CONTROL Walk On Beach	0	0	3	23	14	14	24	25	16
CONTROL Black Point Beach	0	0	5	25	26	19	22	24	15
Stewarts Point SMR	0	0	2	12	2	11	15	14	2
Russian River SMRMA	0	0	3	18	14	26	17	21	15
Russian River SMCA	0	0	5	32	24	34	34	38	18

CONTROL Miwok Beach	0	0	2	21	22	25	27	22	15
CONTROL Salmon Creek Beach	0	0	3	12	19	23	25	23	12
CONTROL Doran Beach	0	0	5	27	25	26	25	23	14
Bodega Head SMR	0	0	4	42	38	39	48	40	11
CONTROL Pinnacle Gulch	0	0	3	15	12	13	18	10	5
CONTROL Dillon Beach	0	0	5	26	21	21	25	19	15
CONTROL Brazil Beach	0	0	5	24	25	22	21	22	14
CONTROL Point Reyes Beach A	0	0	4	27	26	24	25	24	8
CONTROL Tomasini Creek Ranch	0	0	4	23	23	25	21	12	13
CONTROL Point Reyes Beach B	0	0	5	23	23	21	20	19	9
CONTROL Point Reyes Beach C	0	0	4	25	25	25	22	22	8
Point Reyes SMR	0	1	34	100	63	79	133	100	45
Estero de Limantour SMR	0	0	13	59	34	49	83	67	28
Control PRSOUTH	0	0	9	22	4	12	44	23	11
CONTROL Limantour Beach East	0	0	4	25	18	21	23	18	5
Corte Madera Marsh SMP	0	0	0	16	37	31	16	16	14
CONTROL Bolinas Lagoon, Dipsea Road	0	0	4	23	25	26	24	21	9
CONTROL Seadrift	0	0	4	20	14	16	25	18	9
Duxbury Reef SMCA	0	0	3	33	91	74	48	62	88
CONTROL Muir Beach	0	0	5	19	13	8	19	9	13
CONTROL Rodeo Beach	0	0	4	25	26	25	25	21	19
CONTROL Kirby Cove	0	0	4	17	21	10	24	11	5

CONTROL Baker Beach	0	0	4	12	5	9	3	2	17
CONTROL China Beach	0	0	0	24	15	11	14	2	14
CONTROL Land's End	0	0	2	10	11	12	11	13	10
CONTROL Ocean Beach North	0	0	5	24	26	25	23	17	9
CONTROL Ocean Beach Central	0	0	4	15	13	14	19	23	13
CONTROL Thornton Beach North	0	0	4	18	12	15	11	8	5
CONTROL Sharp Park	0	0	5	24	25	24	21	22	12
CONTROL South Montara Beach	0	0	4	25	25	23	24	23	14
Montara SMR	0	0	16	100	97	89	82	72	29
CONTROL Pillar Point, Mavericks	0	0	5	27	24	20	26	24	13
CONTROL Half Moon Bay, Naples Beach	0	0	4	26	27	26	26	22	15
CONTROL Half Moon Bay, Frances Beach	0	0	4	25	23	14	10	12	0
CONTROL Pomponio Headlands	0	0	2	12	13	23	16	21	5
CONTROL Pescadero Beach	0	0	4	24	25	25	23	23	11
CONTROL Pebble Beach	0	0	4	24	24	21	24	19	10
Control Bean Hollow	0	0	40	58	16	0	0	0	0
Ano Nuevo SMCA	0	0	34	96	70	65	71	57	25
Control Coastal Bluffs	0	0	39	45	84	31	0	0	0
CONTROL Seacliff State Beach	0	0	0	0	0	0	0	29	208
Natural Bridges SMR	0	0	34	55	107	11	0	0	0
CONTROL Natural Bridges	0	0	0	0	0	0	0	19	6

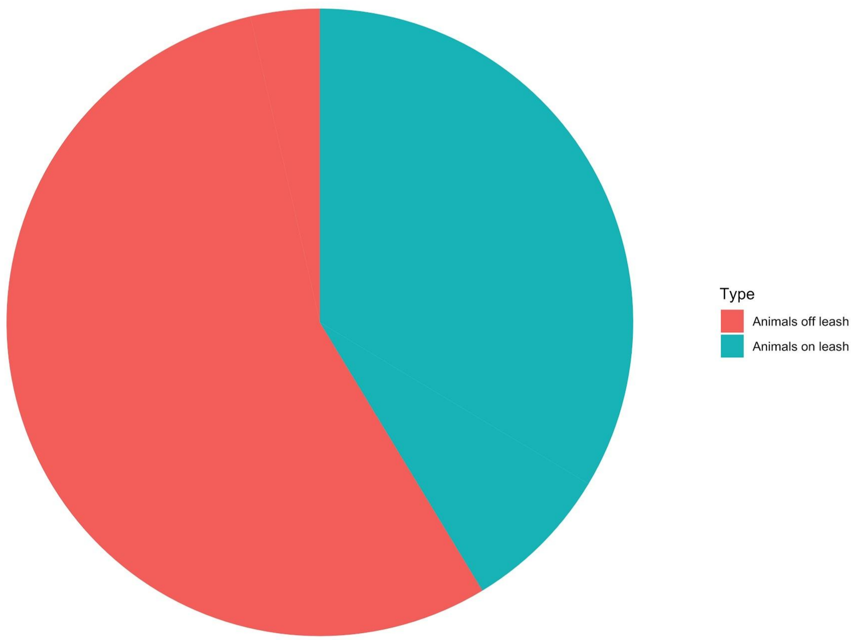
State Park									
Asilomar SMR	0	0	61	163	131	25	21	33	22
Lovers Point SMR	0	0	102	135	161	27	14	36	23
Control 17 Mile Drive	0	0	28	77	72	27	23	13	3
Point Lobos SMR	0	0	49	88	72	11	12	11	8
Control Malpaso	0	0	18	63	46	11	9	1	0
Cambria SMCA	0	0	51	54	177	26	3	2	0
Control Montana de Oro	0	0	50	113	97	40	33	10	0
Point Buchon SMR	0	0	12	27	32	8	0	0	0
Kashtayit SMCA	0	36	74	90	78	71	83	100	76
Control KWEST	0	18	38	44	39	35	42	51	37
Naples SMCA	4	31	60	77	51	34	41	70	34
Control NPEAST	0	18	35	39	22	17	42	53	25
Control CPWEST	1	19	49	61	41	29	24	54	43
Control CPEAST	20	33	81	83	53	37	55	60	32
Control ABWEST	0	0	5	0	0	0	0	0	0
Control ABEAST	0	0	6	0	0	0	0	0	0
Campus Point SMCA	49	117	329	334	237	172	286	340	309
Control CARPW	0	0	2	0	33	14	9	0	0
Control CARPE	0	0	2	0	30	14	9	0	0
Control LEO	0	4	13	9	0	0	0	0	0
Control OW	12	66	27	12	11	4	3	4	2
Point Dume SMCA	108	206	169	144	123	51	70	93	65
Control OE	27	86	41	36	21	11	13	9	5

Point Dume SMR	207	224	191	262	168	79	118	86	58
Control PVON1	49	88	84	88	73	58	51	89	78
Point Vicente SMCA	116	177	193	176	115	123	121	188	164
Abalone Cove SMCA	62	113	94	90	65	68	76	99	110
Control PVOS1	27	61	36	36	35	41	35	46	64
Upper Newport Bay SMCA	0	0	77	90	100	84	82	128	81
Crystal Cove SMCA	0	0	56	87	93	109	70	156	156
Laguna Beach SMR	0	0	175	186	175	147	101	252	231
Laguna Beach SMCA	0	0	28	22	39	42	34	84	68
Dana Point SMCA	0	0	68	62	38	53	64	48	58
Blue Cavern (Catalina Island) SMCA	0	0	0	0	0	11	4	0	0
Cat Harbor (Catalina Island) SMCA	0	0	0	0	0	4	2	0	0
Swami's SMCA	0	6	47	28	0	2	30	100	130
San Diego-Scripps Coastal SMCA	0	8	25	7	0	5	16	8	10
Matlahuayl SMR	0	10	12	7	2	15	20	27	13
South La Jolla SMR	0	0	0	0	0	0	16	26	35
Control Outside Boundary 1 (TRM)	0	8	0	0	1	2	7	43	3
Control Outside Boundary 2 (TRM)	0	0	1	0	6	0	4	16	2
Tijuana River Mouth SMCA	0	55	136	45	25	12	3	9	1

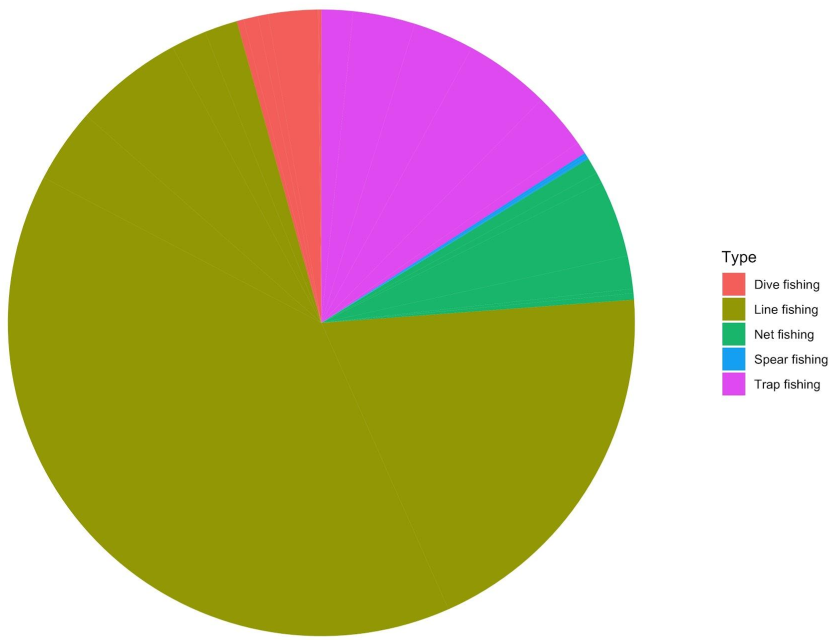
Breakdowns of Activity Categories

The following charts show the relative proportions of specific activities in each of the seven large categories used in our analysis.

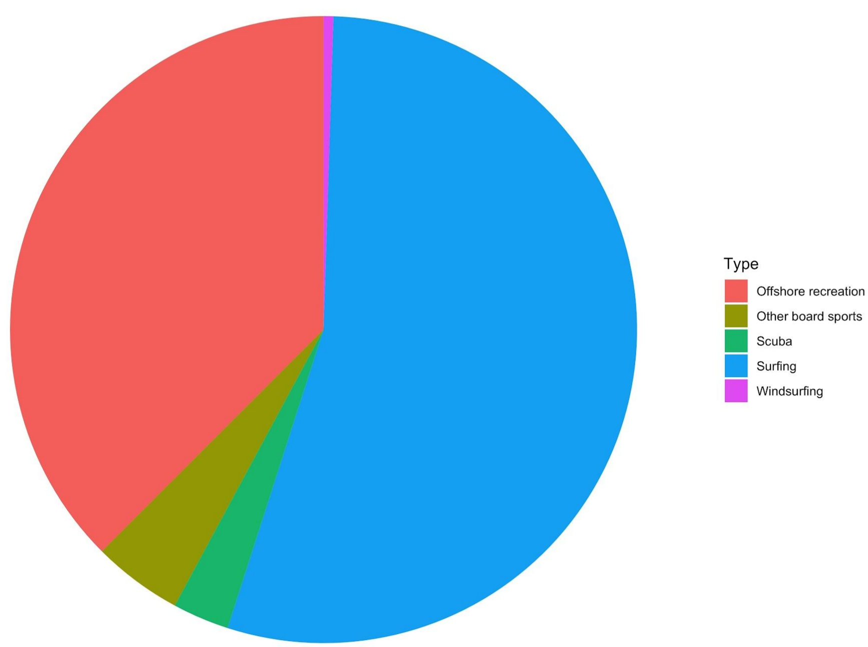
Domestic animals



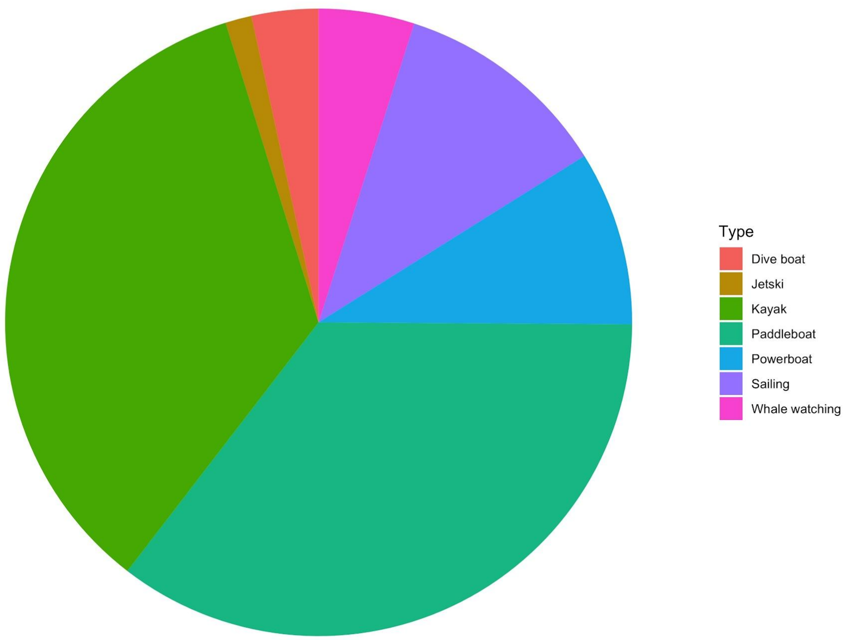
Offshore fishing



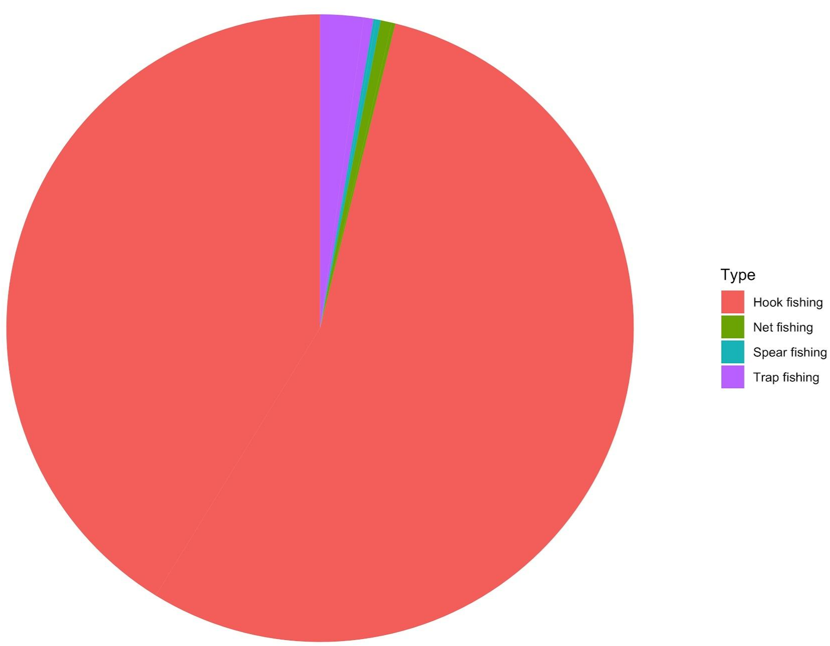
Offshore recreation



Recreational Boating



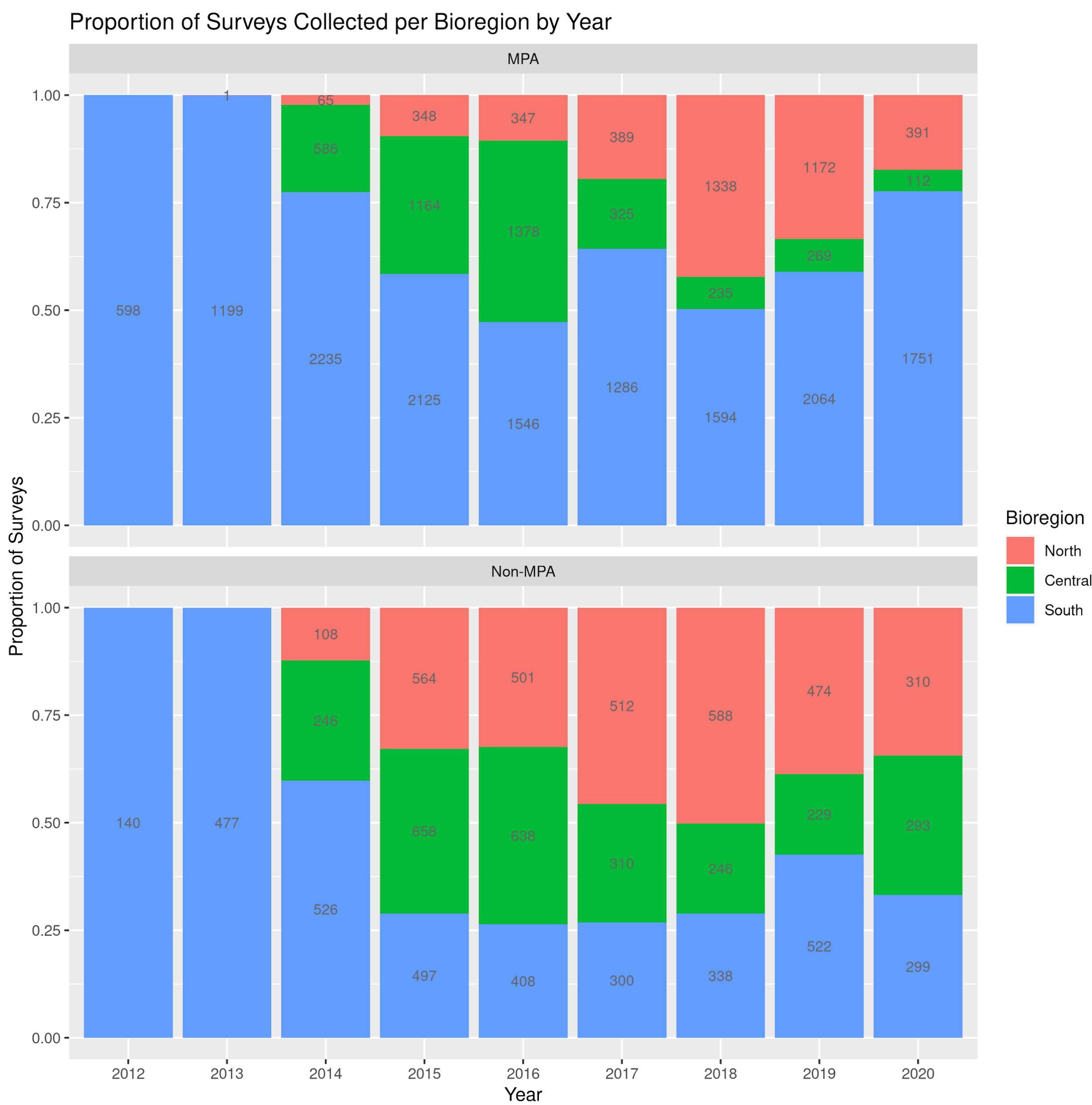
Onshore fishing



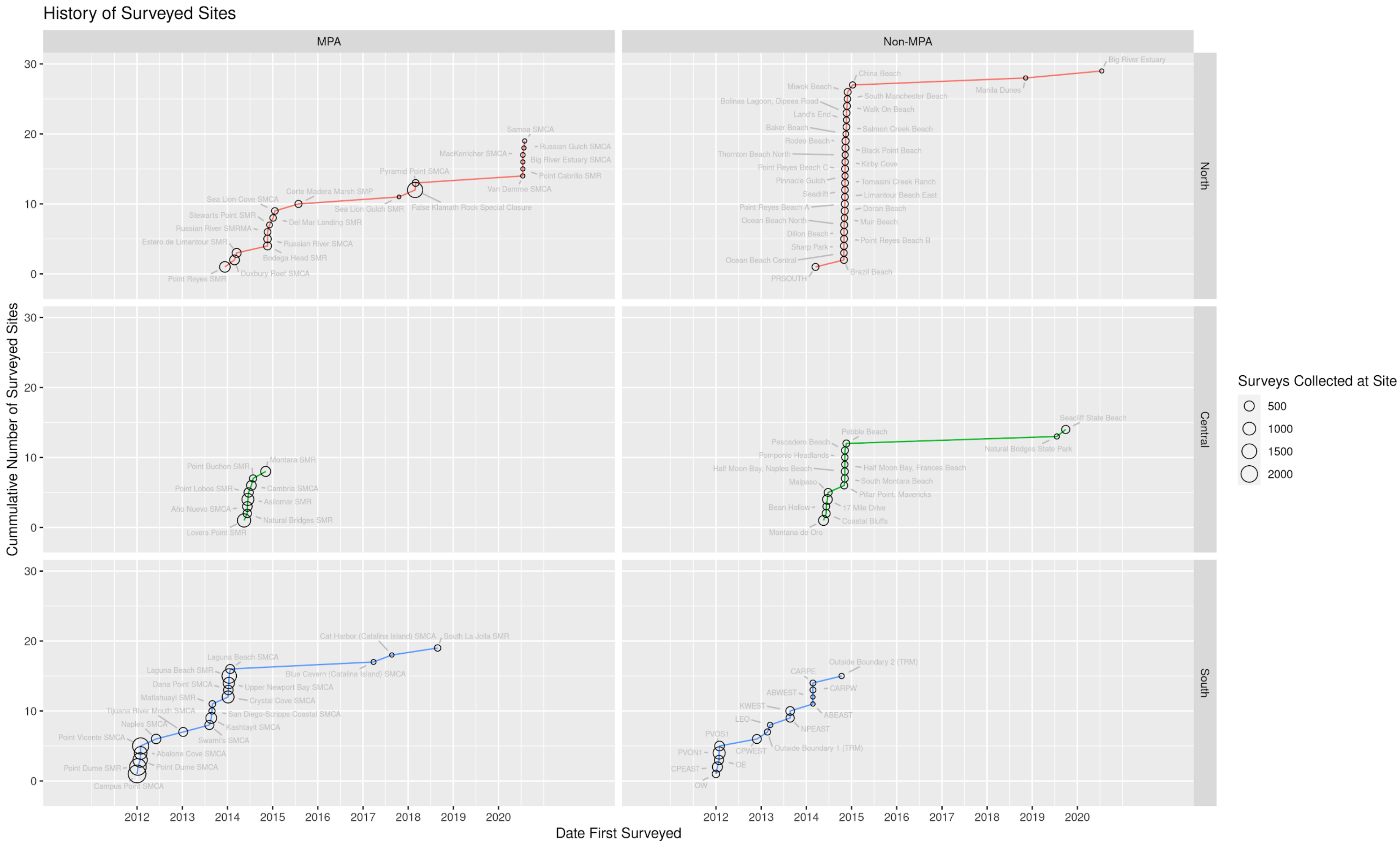
Data summaries by bioregion

Figures in this section summarize MPA Watch data in a variety of ways through the lens of MPA bioregions.

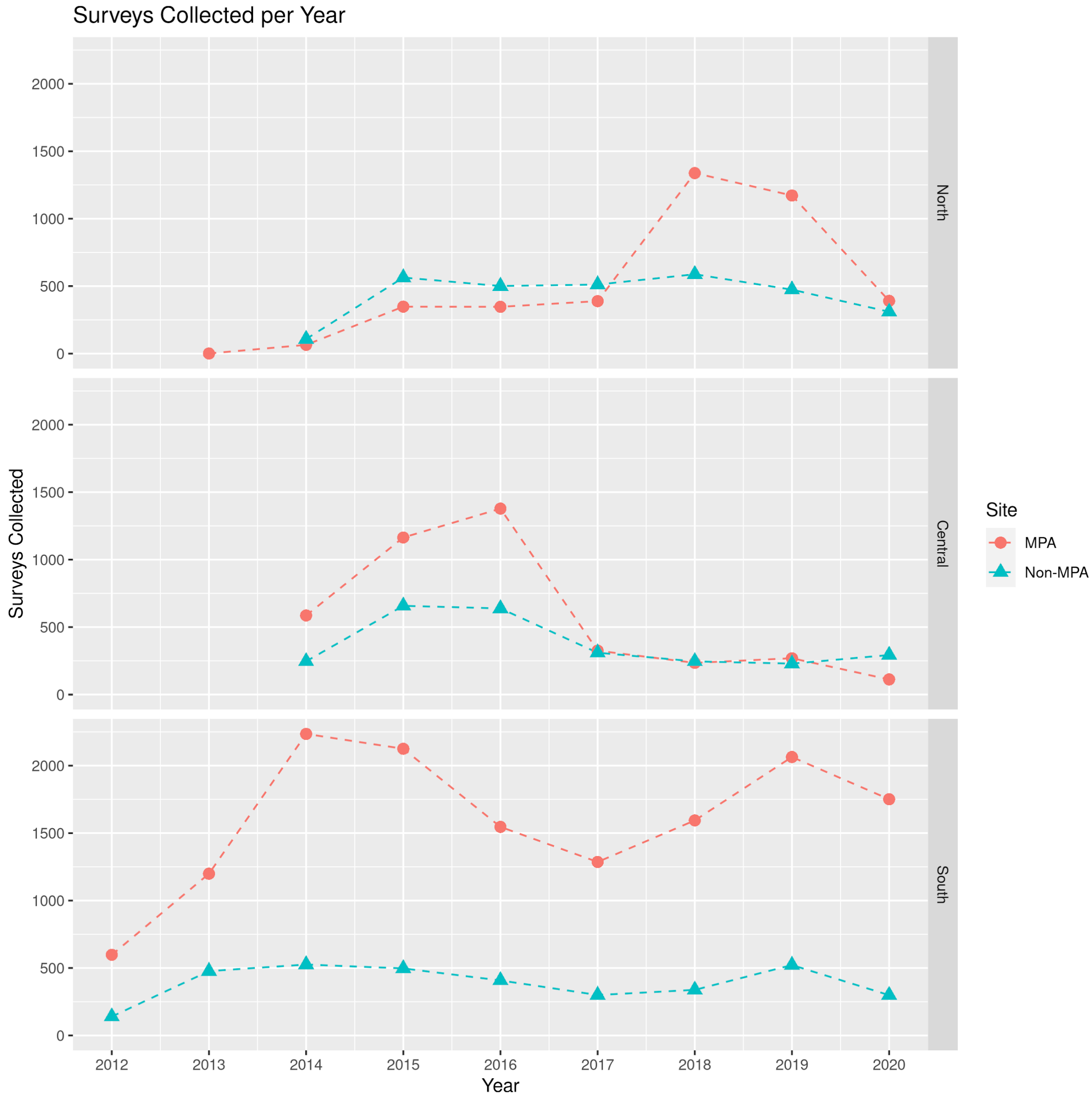
Proportion of surveys collected per bioregion by year



History of surveyed sites in each bioregion

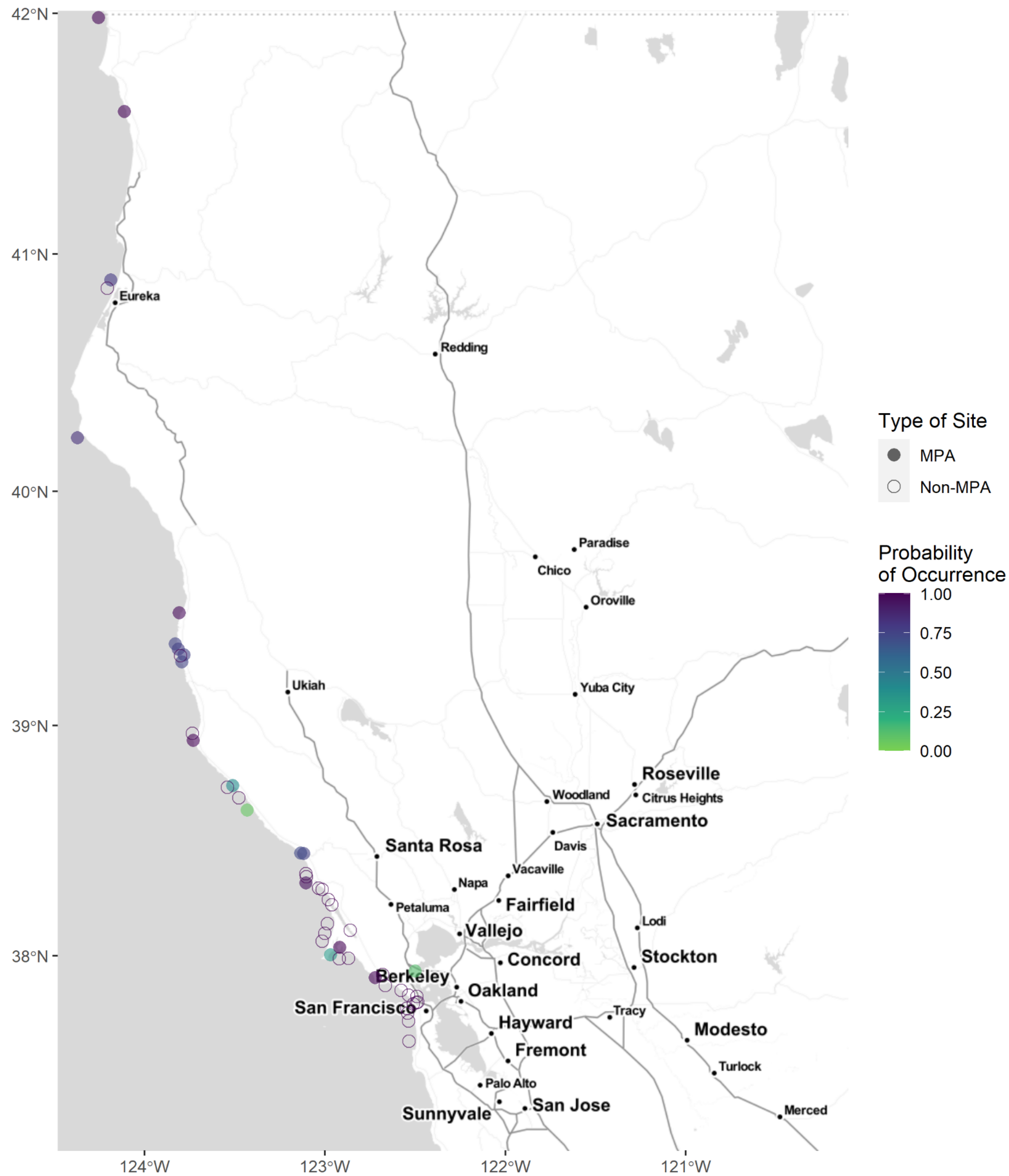


Surveys collected per year in each bioregion

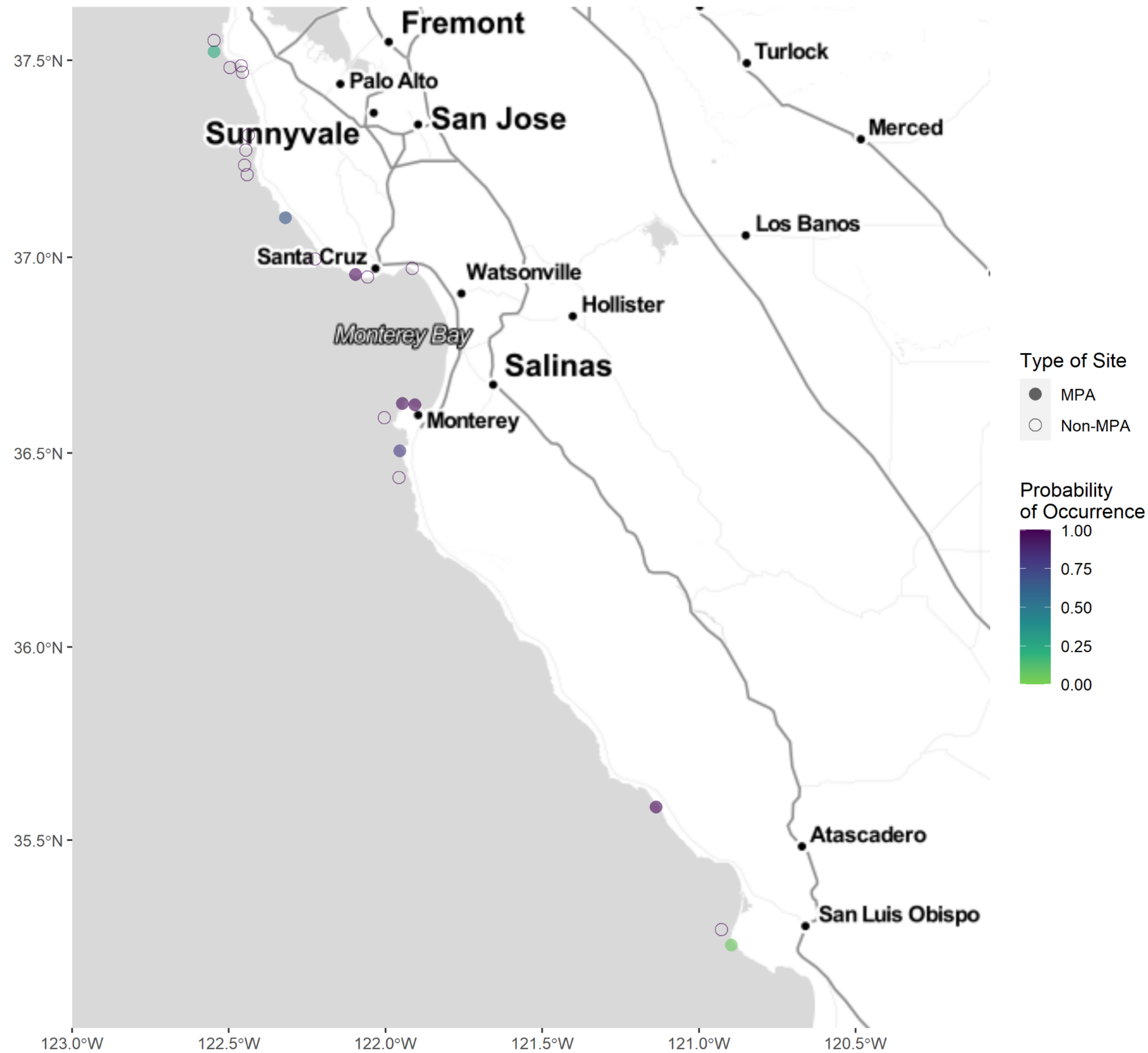


Occurrence probability for each site, broken down by bioregion

Onshore fishing - North Coast

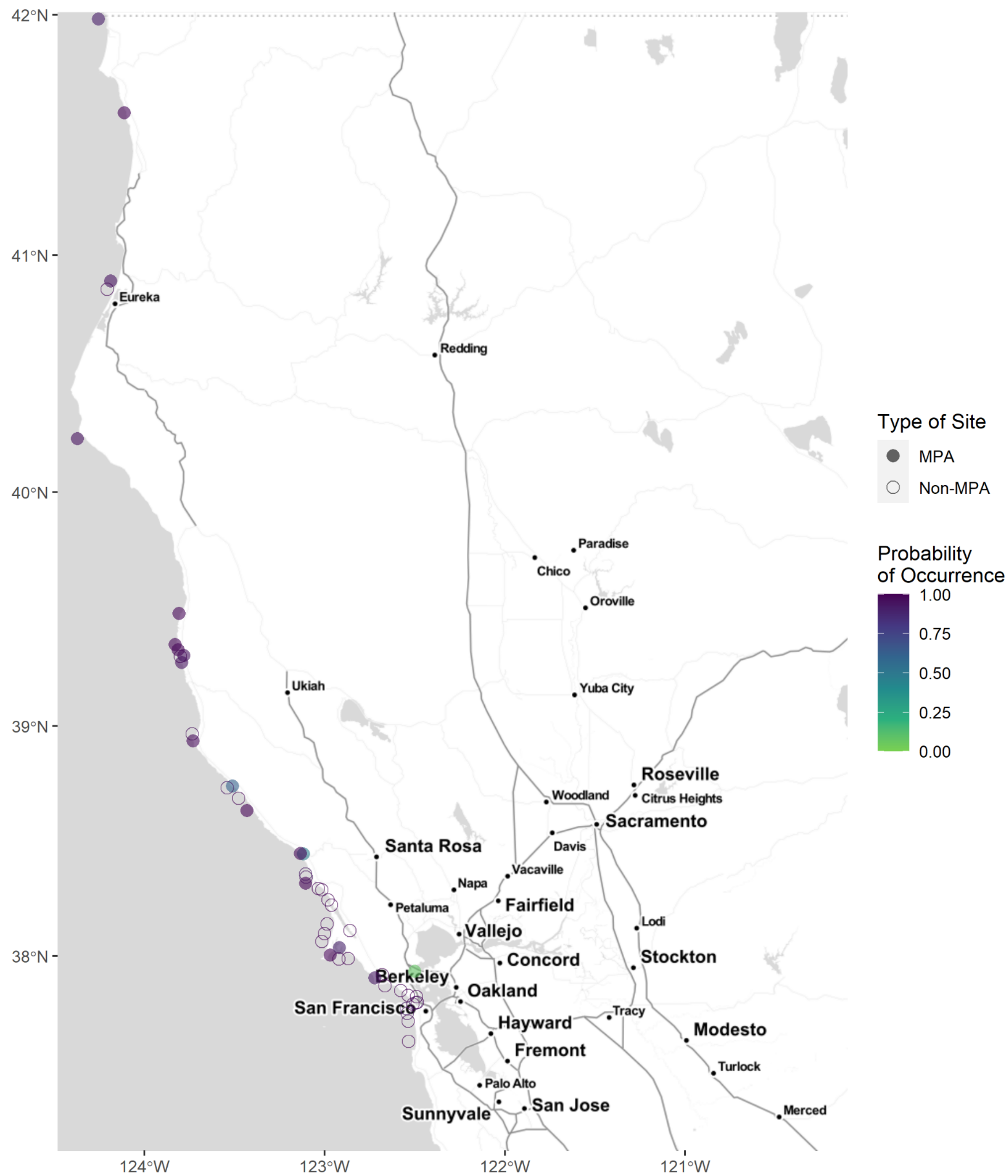


Onshore Fishing - Central Coast

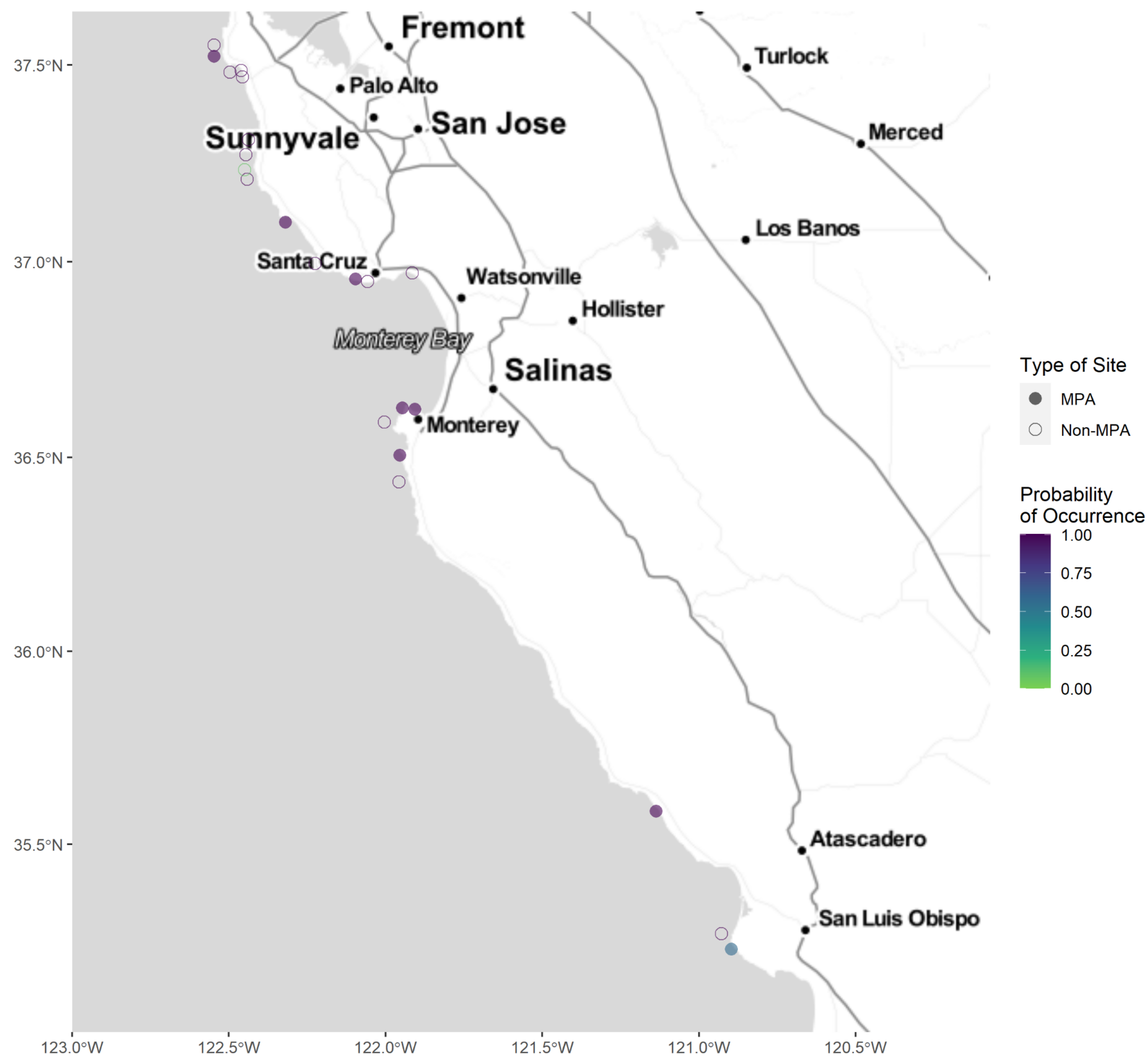


Onshore Fishing - South Coast

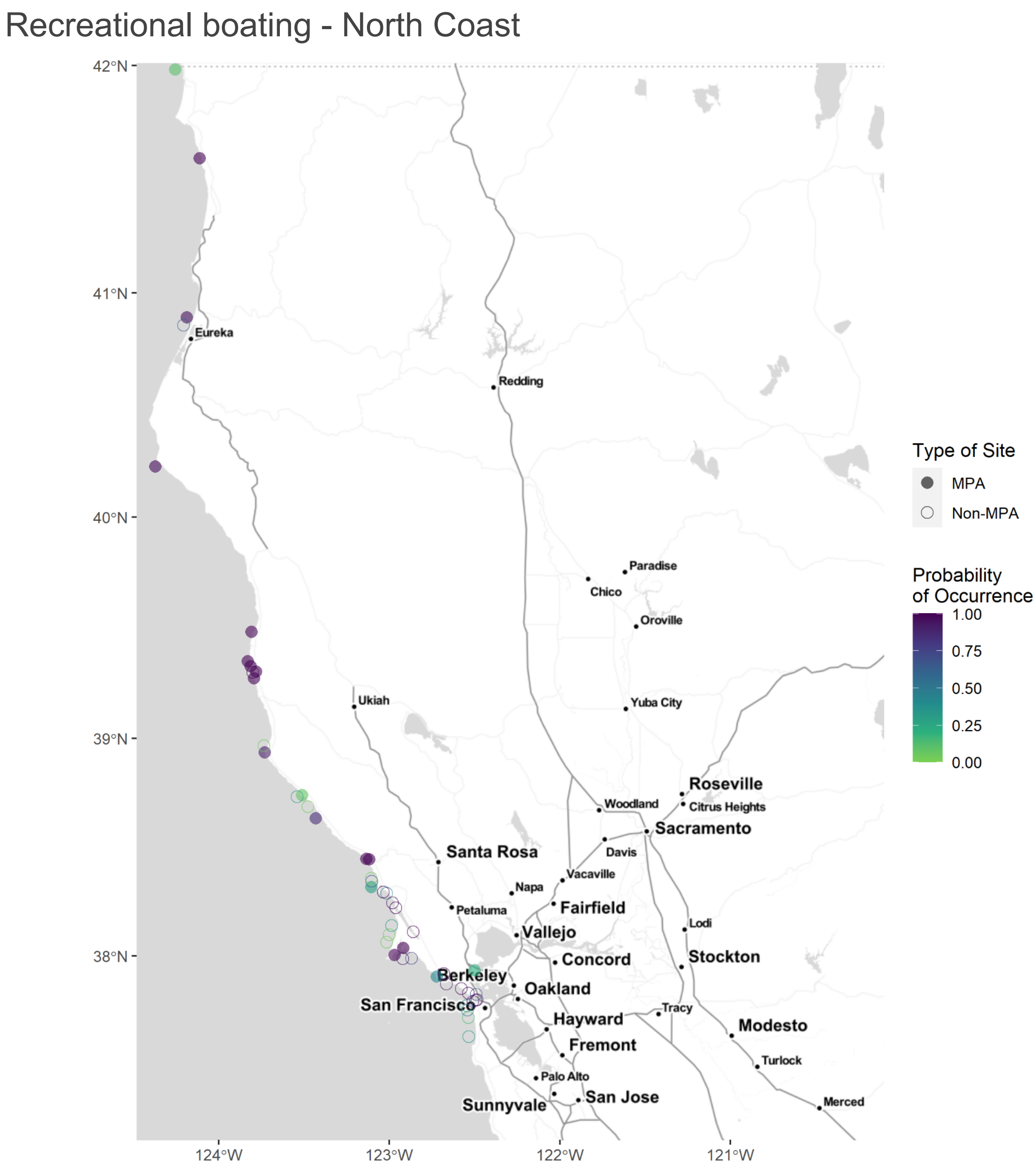
Offshore fishing - North Coast



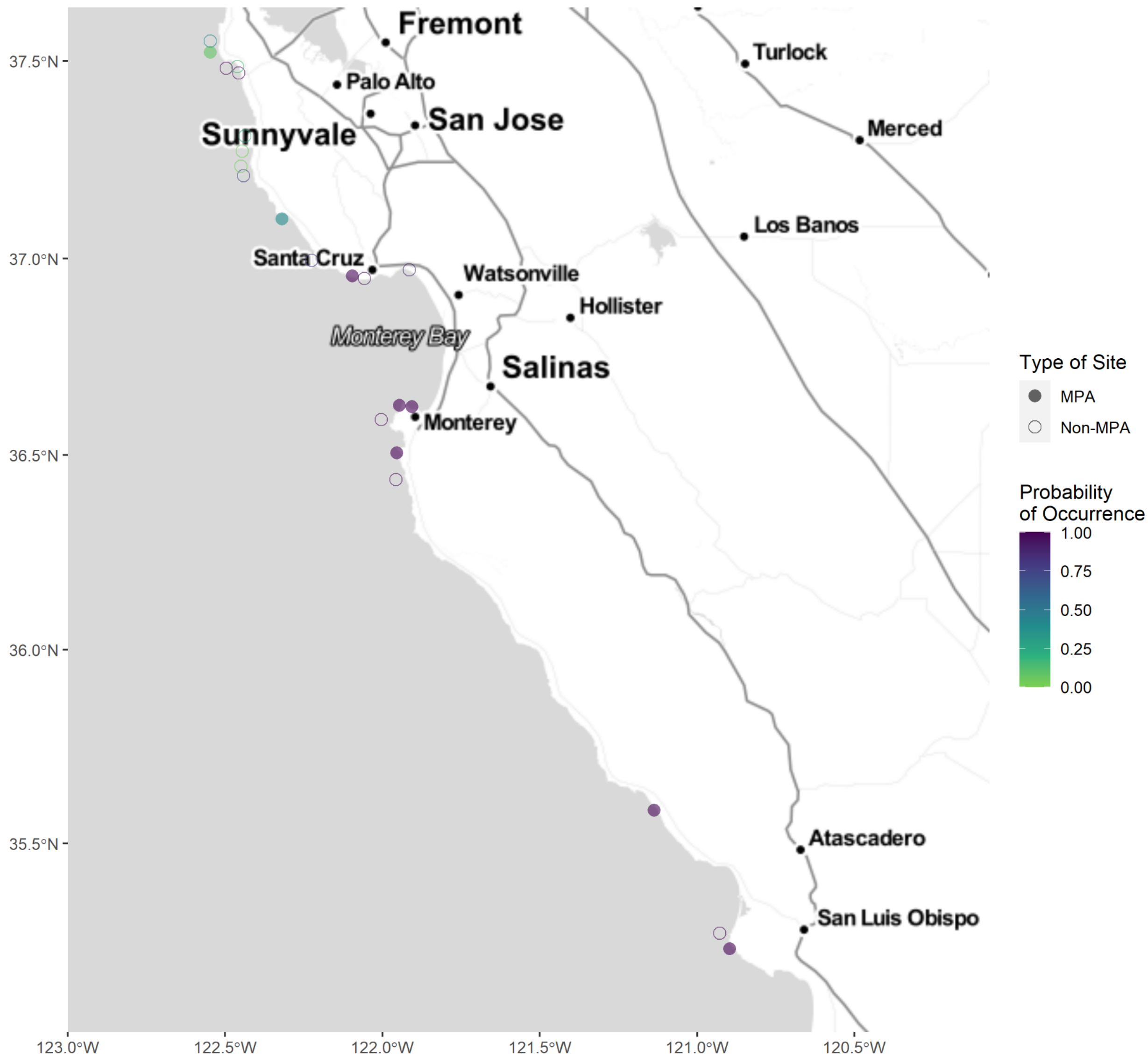
Offshore fishing - Central Coast



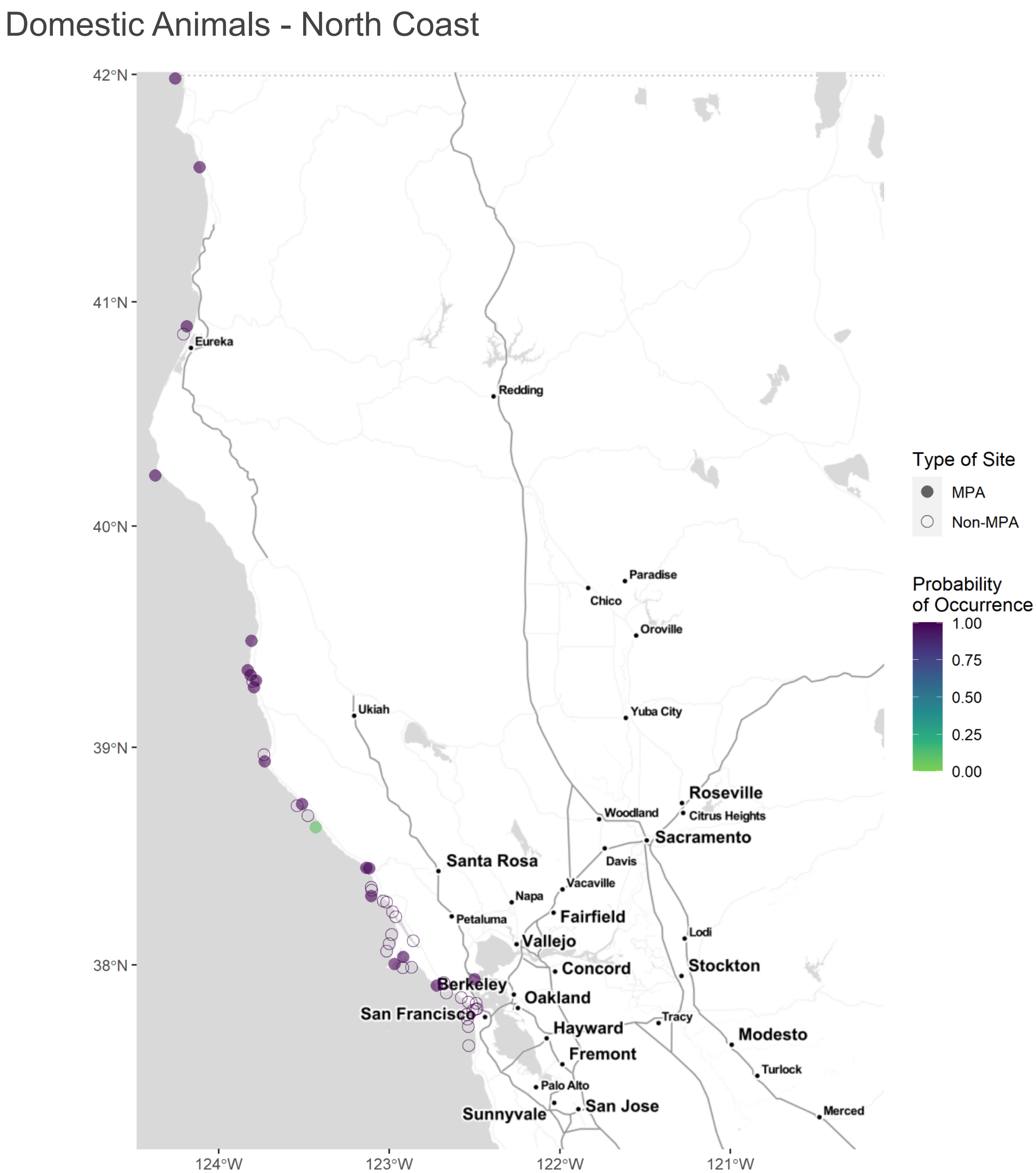
Offshore fishing - South Coast


Recreational boating - North Coast
42°N
41°N
40°N
39°N
38°N
124°W
123°W
122°W
121°W
Eureka
Redding
Paradise
Chico
Oroville
Ukiah
Yuba City
Roseville
Woodland
Citrus Heights
Sacramento
Santa Rosa
Davis
Vacaville
Napa
Petaluma
Fairfield
Vallejo
Lodi
Concord
Stockton
Berkeley
Oakland
San Francisco
Tracy
Hayward
Modesto
Fremont
Turlock
Palo Alto
San Jose
Sunnyvale
Merced
Type of Site
MPA
Non-MPA
Probability
of Occurrence
1.00
0.75
0.50
0.25
0.00

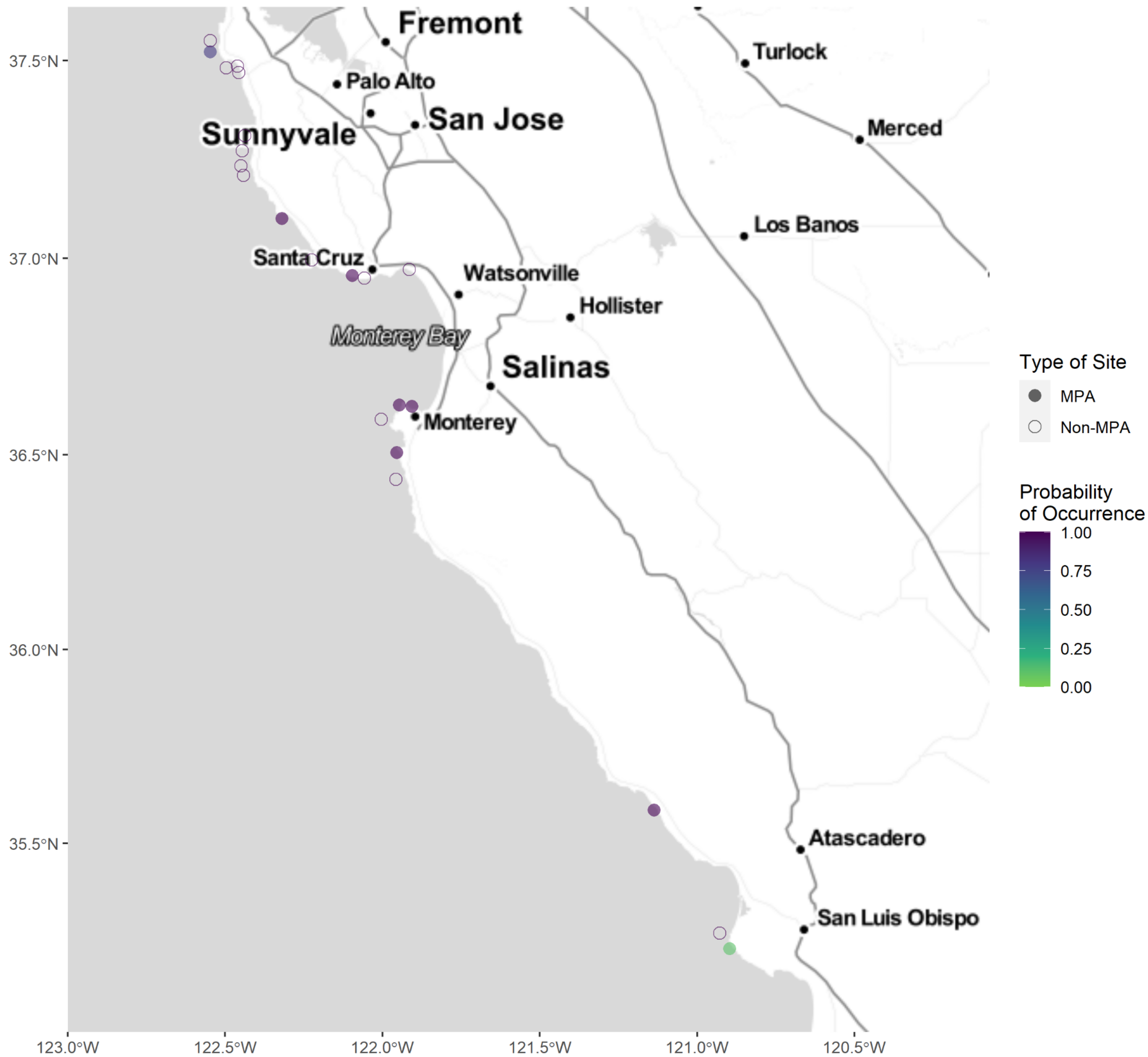
Recreational boating - Central Coast



Recreational boating - South Coast

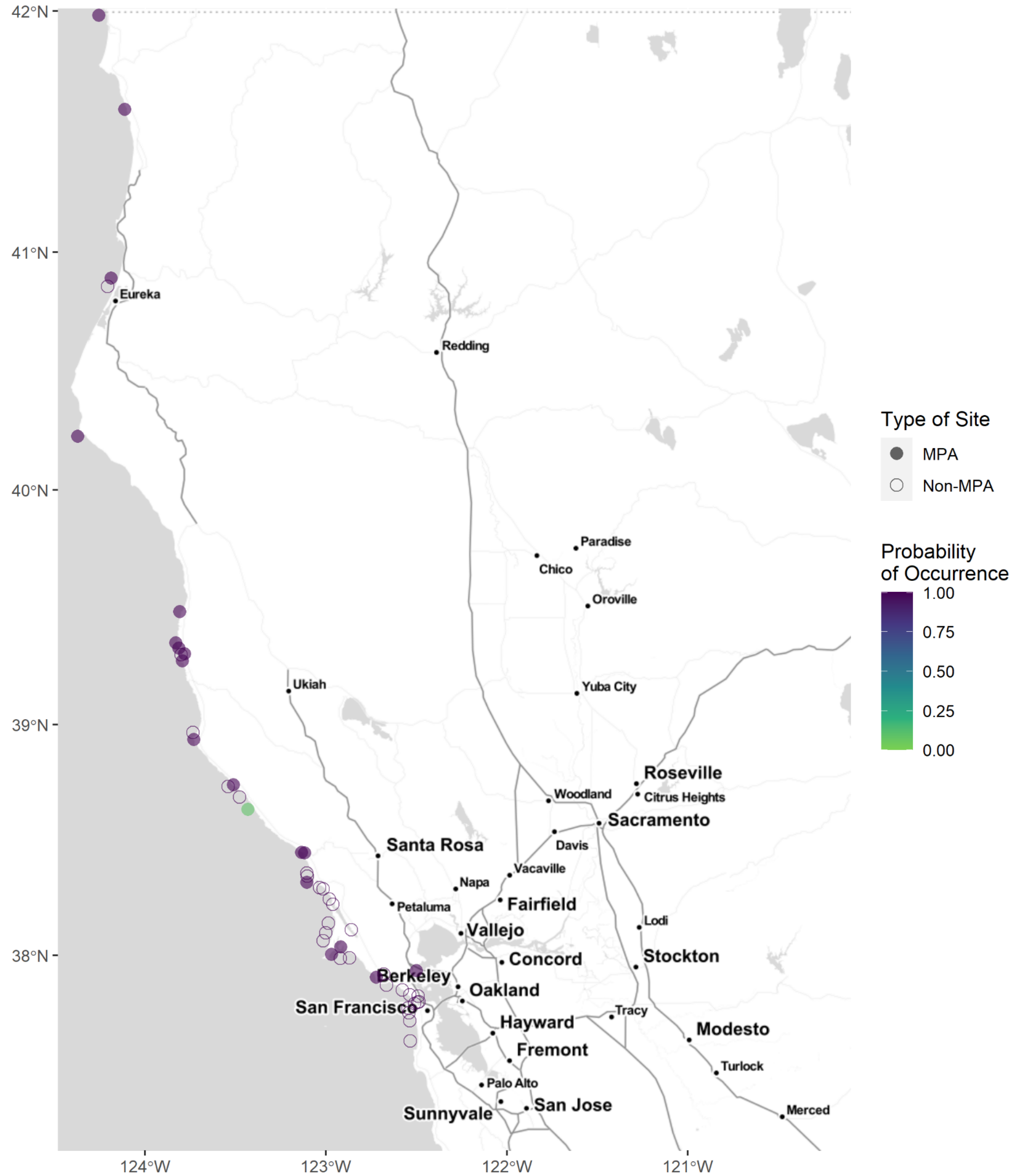

Domestic Animals - North Coast
42°N
41°N
40°N
39°N
38°N
124°W
123°W
122°W
121°W
Eureka
Redding
Paradise
Chico
Oroville
Ukiah
Yuba City
Roseville
Woodland
Citrus Heights
Sacramento
Santa Rosa
Davis
Vacaville
Napa
Petaluma
Fairfield
Vallejo
Lodi
Concord
Stockton
Berkeley
Oakland
San Francisco
Tracy
Hayward
Modesto
Fremont
Turlock
Palo Alto
San Jose
Sunnyvale
Merced
Type of Site
MPA
Non-MPA
Probability of Occurrence
1.00
0.75
0.50
0.25
0.00

Domestic Animals - Central Coast

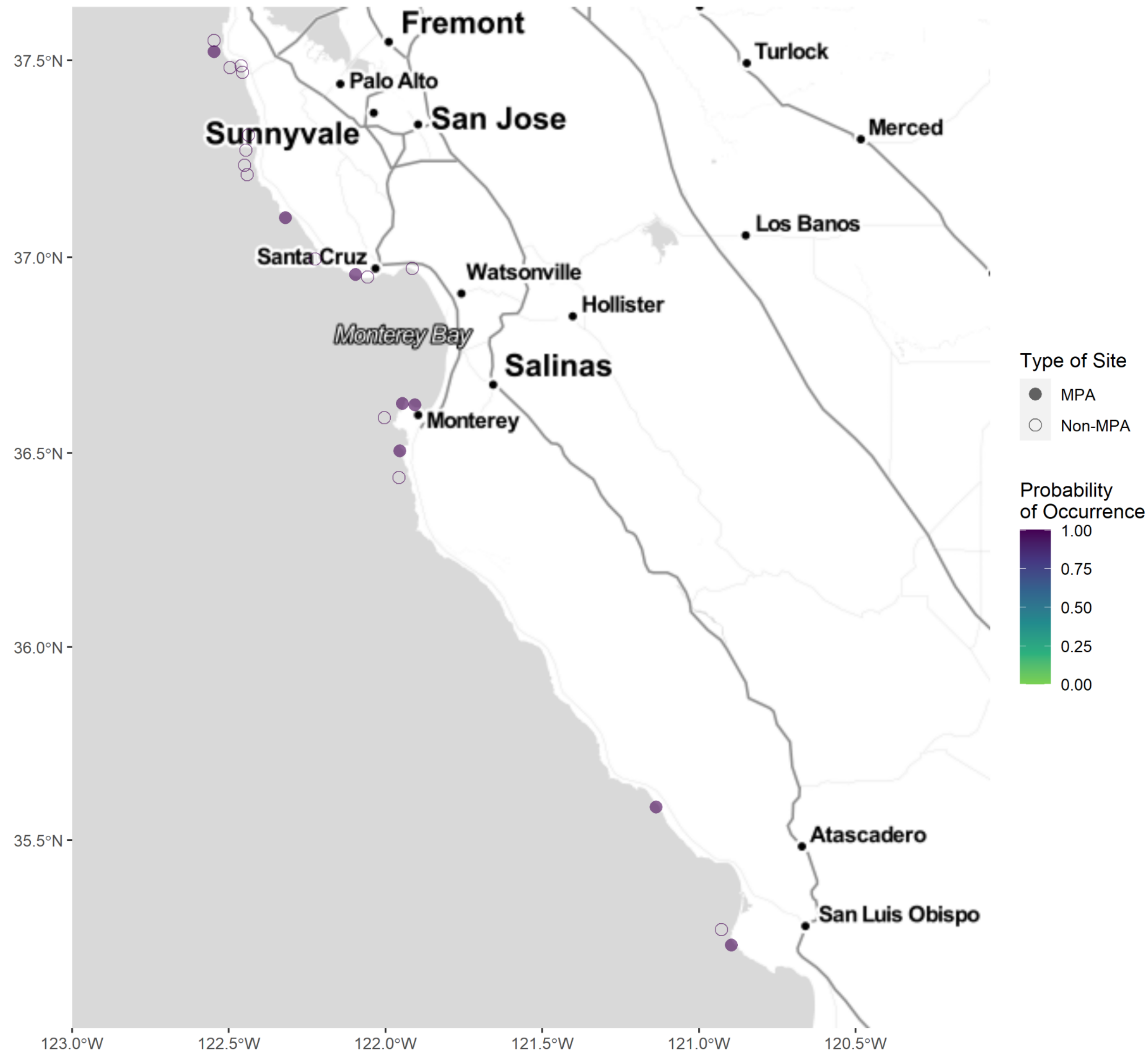


Domestic Animals - South Coast

Onshore recreation - North Coast

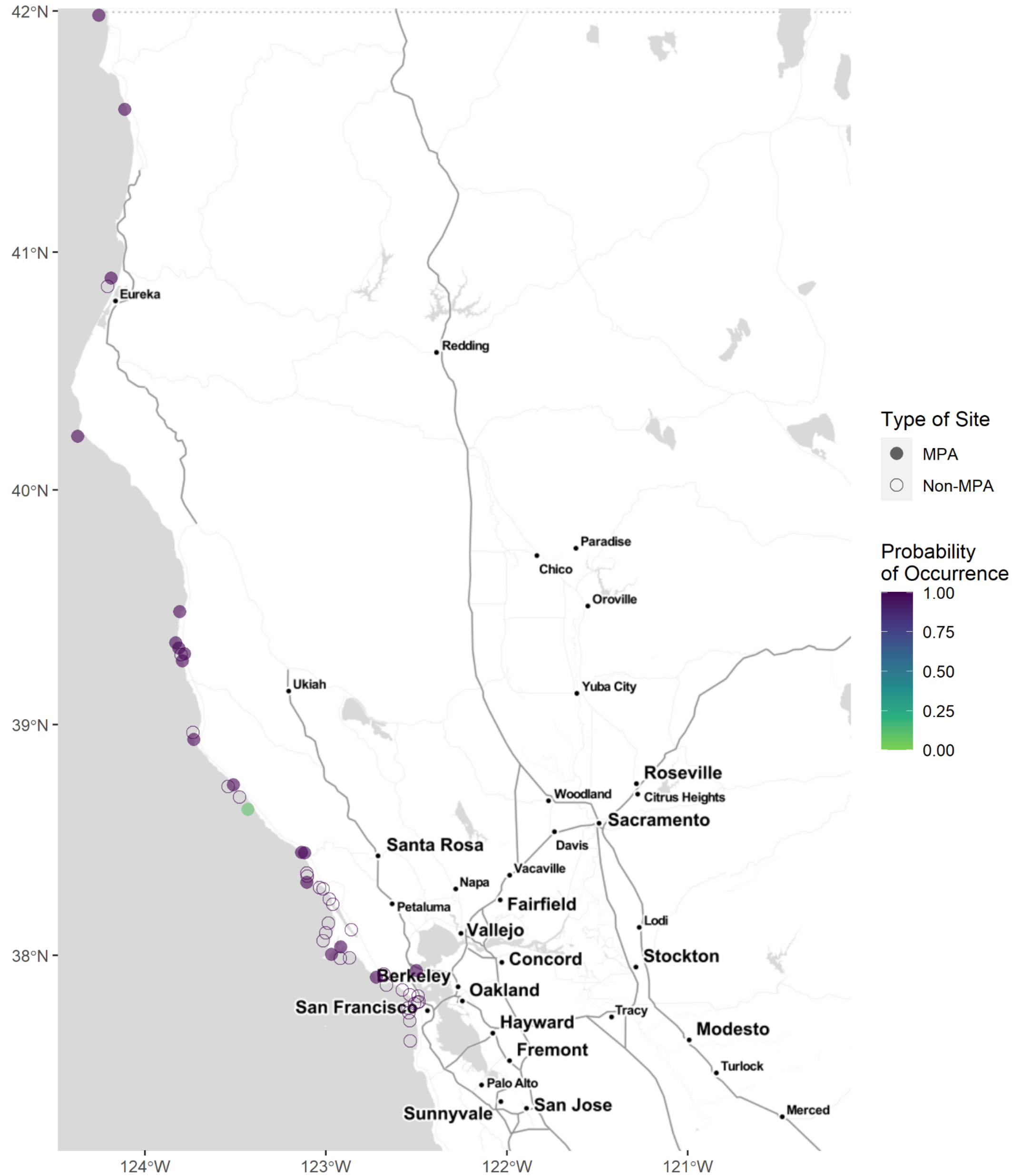


Onshore recreation - Central Coast

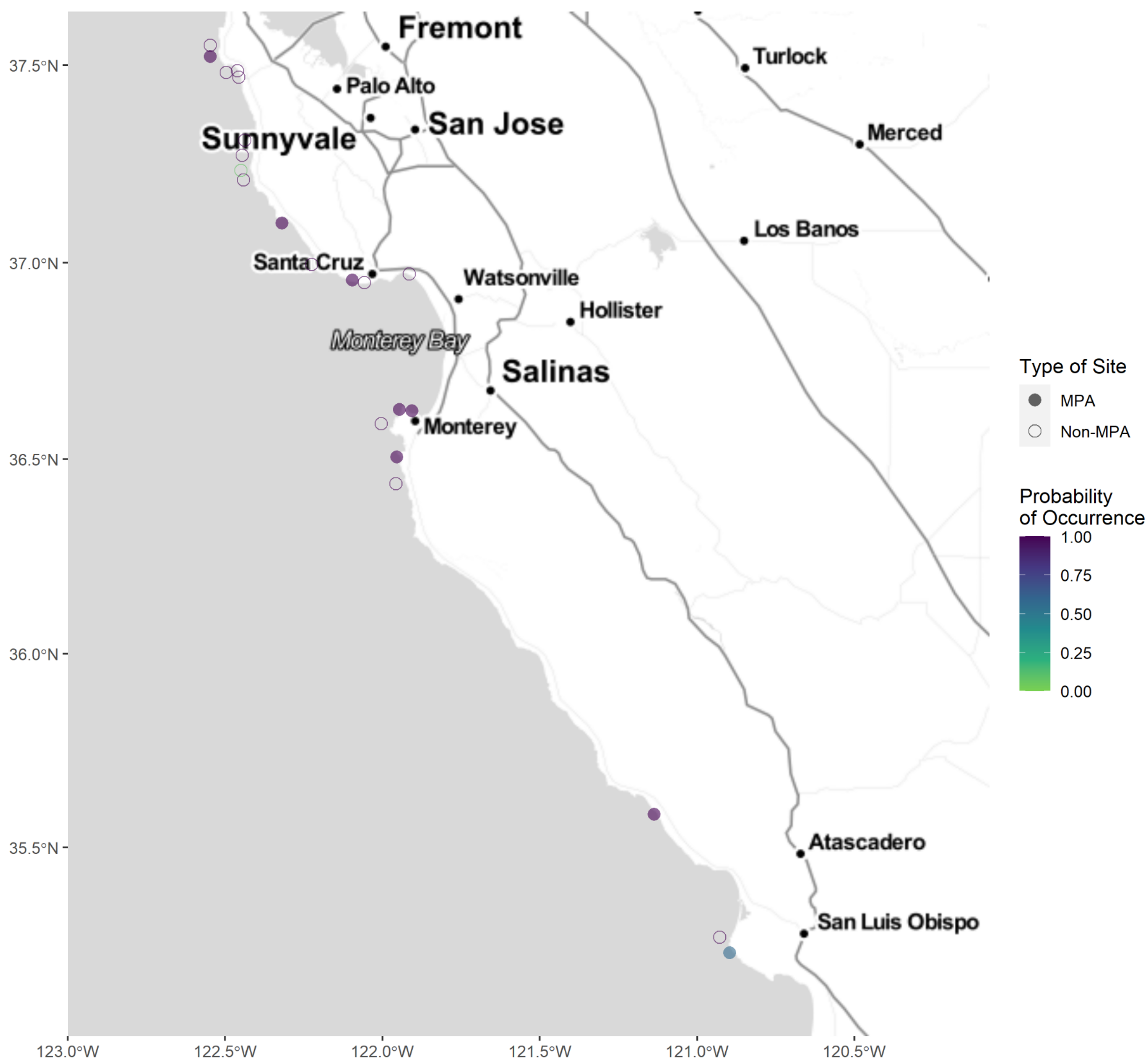


Onshore recreation - South Coast

Offshore Recreation - North Coast

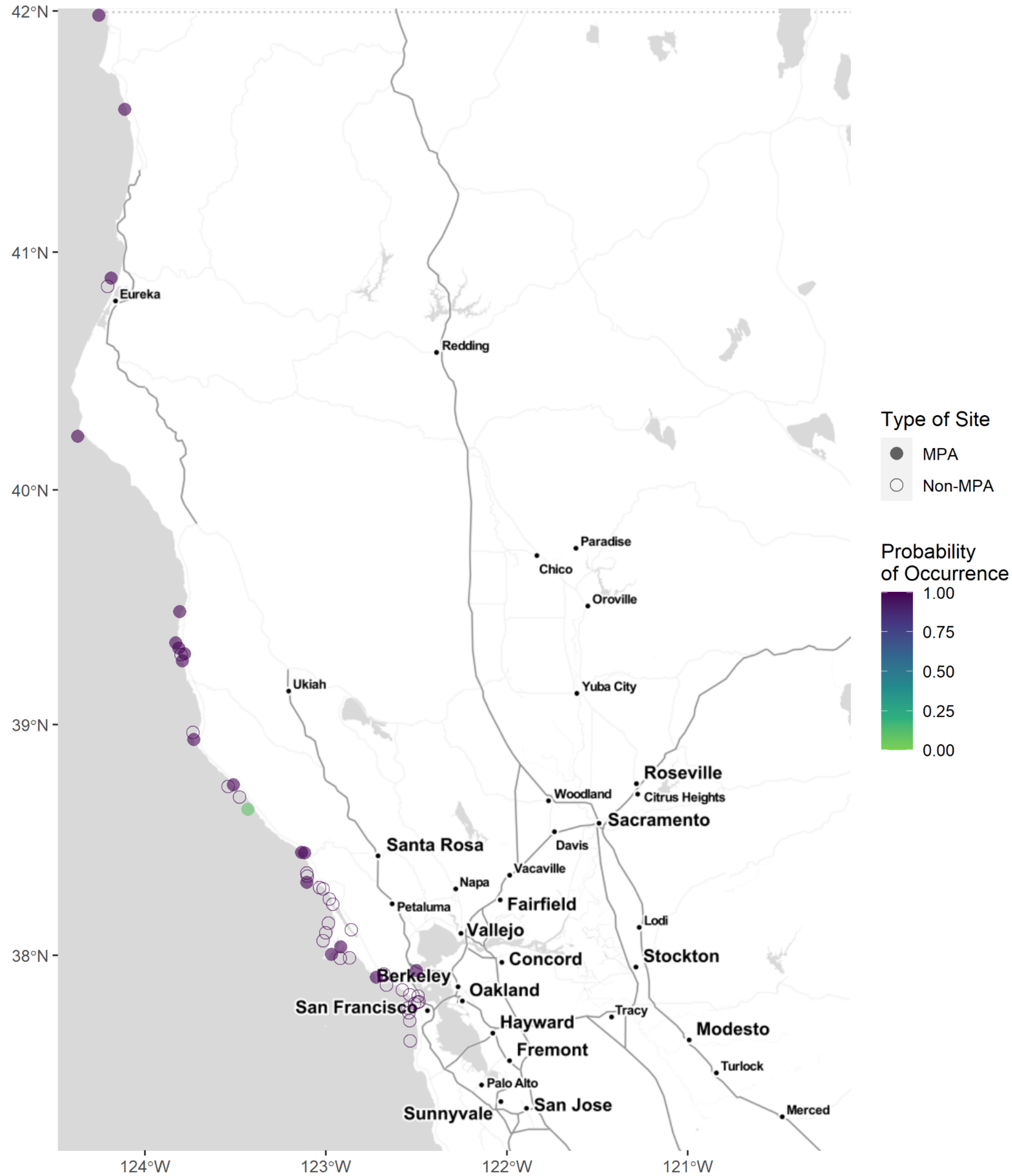


Offshore Recreation - Central Coast

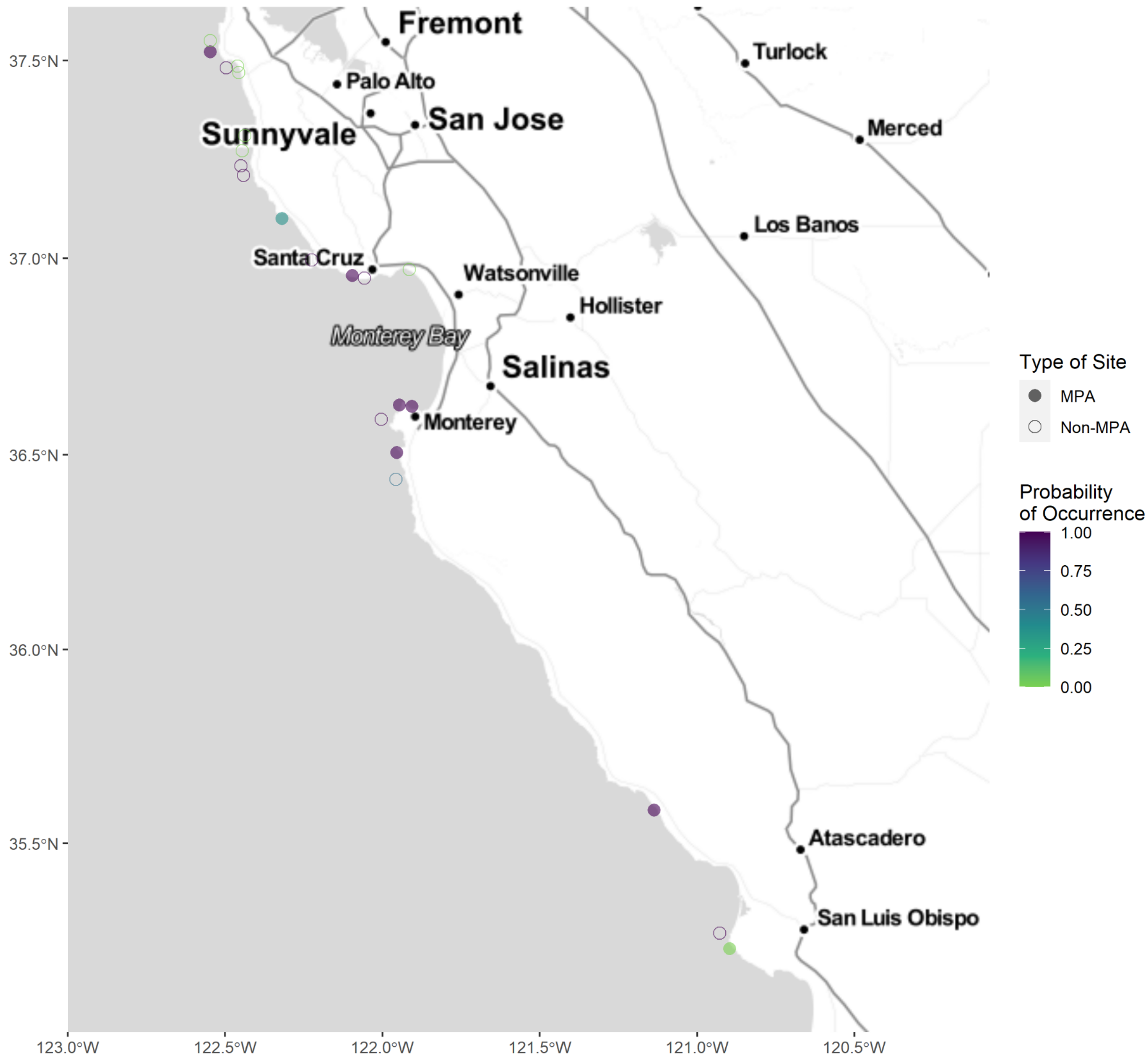


Offshore Recreation - South Coast

Tidepooling - North Coast

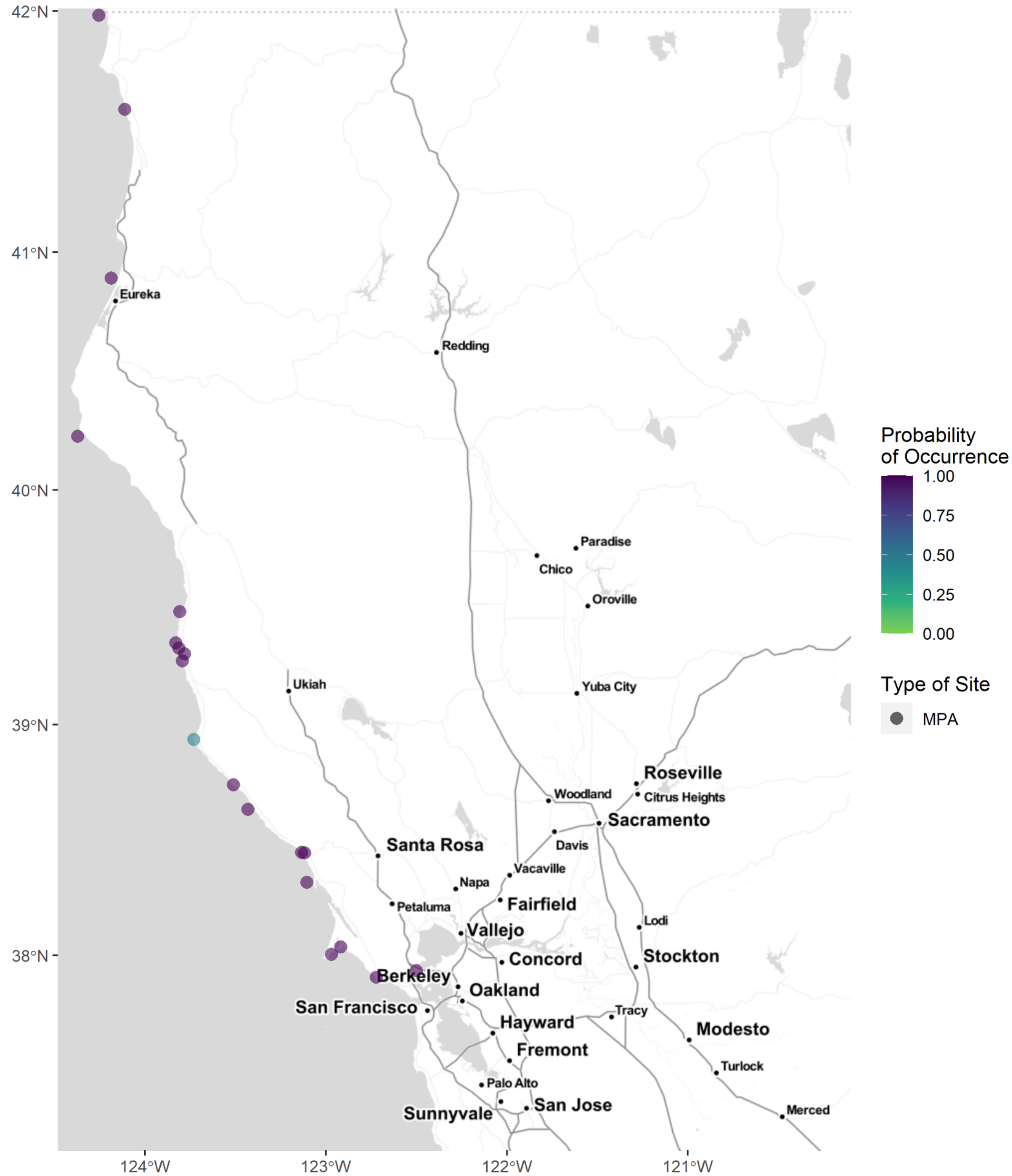


Tidepooling - Central Coast

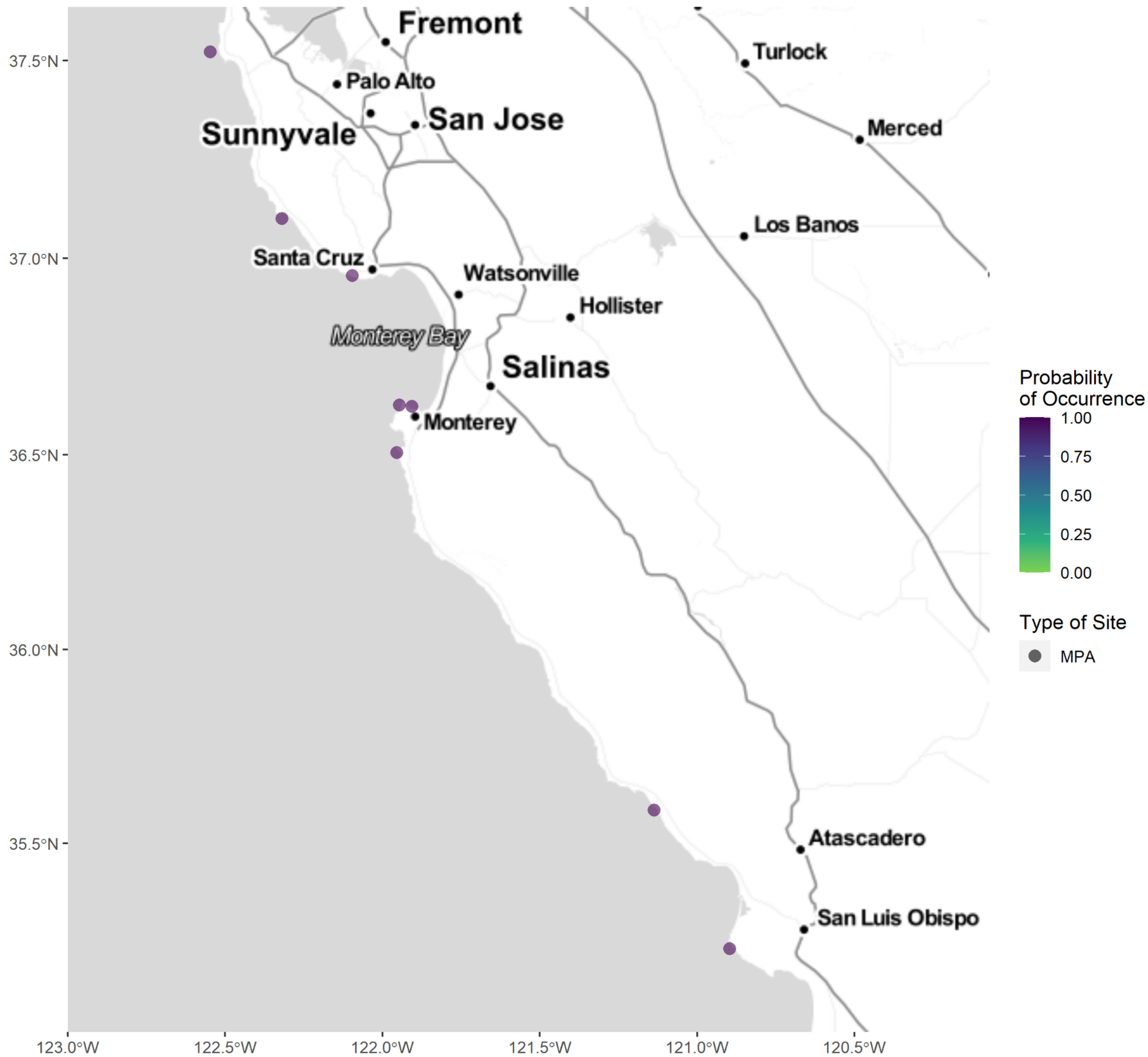


Tidepooling - South Coast

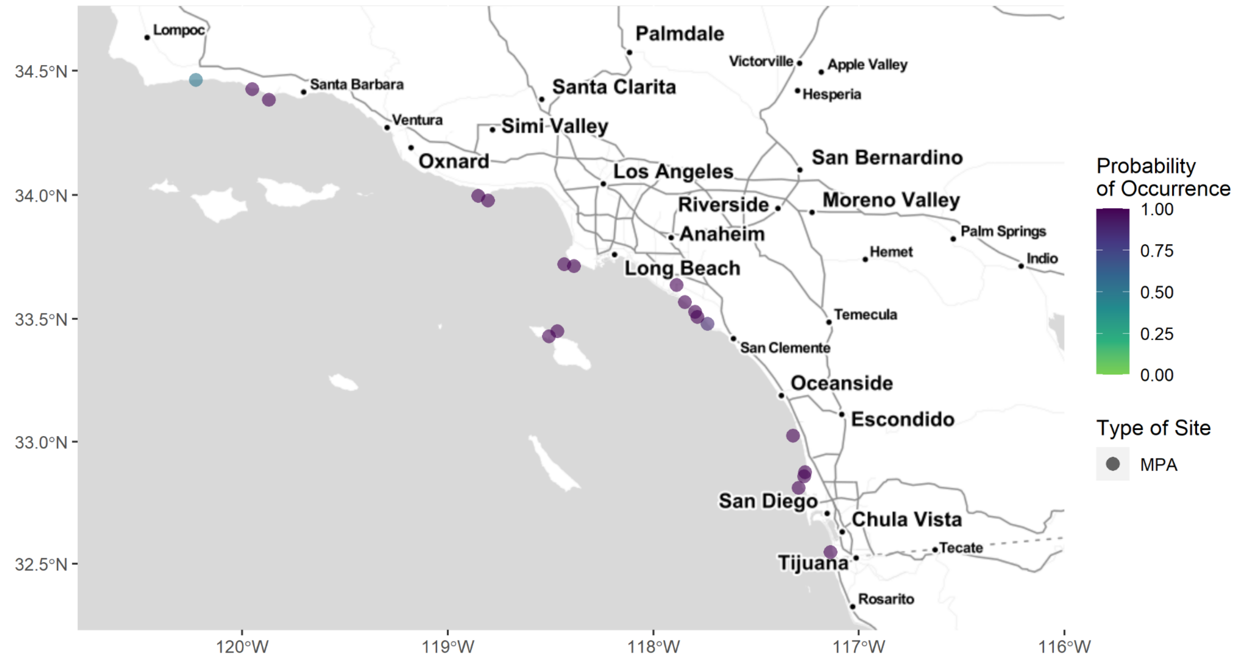
Potential Violations - North Coast



Potential Violations - Central Coast



Potential Violations - South Coast



MPA Watch Occupancy Model Technical Write-Up

January 2022

The goal of this model is to answer questions about Marine Protected Area (MPA) use across the state of California during 2012-2020. Surveyors collect data on human activities in MPAs following a set protocol, but sampling effort is highly variable across space and time.

Modeling approach

We use hierarchical mixture statistical models (specifically, occupancy models) to account for spatial and temporal variation in sampling effort, following the approach of Kéry and Royle (2021)[1] to using Swiss Bird Survey data to understand the distribution of a Swiss woodpecker. The approach explicitly models the detection probability as changing over time and in response to covariates, separately from the actual occurrence of the process of interest. This allows us to estimate the impacts of covariates on either the detection and/or the occurrence processes, and correlation structures at multiple spatial and temporal scales.

We used JAGS (version 4.2.0) to implement these models. JAGS allows us to flexibly construct models that represent the above-mentioned complex processes, covariates, and correlation structures. JAGS uses a Gibbs sampler to implement Markov chain Monte Carlo (MCMC) simulation, trying a range of possible values for each model parameter with a bias towards the values that are most likely. As a Bayesian tool, the user specifies prior probability distributions (representing previous knowledge of each parameter's probable values) and then the data and the proposed statistical structure (likelihood function) inform the most likely values. Valid statistical inference from an MCMC estimation procedure is determined using a combination of visual checking and calculating the Gelman-Rubin diagnostic for model convergence: for each parameter, two or more Markov chains are started from different values and then run for the same number of iterations, and the different chains are compared with each other. If the variance within them is similar to the variance between them, the sampling is considered to have converged and the parameter's posterior distribution (from which we calculate means/point estimates and credible intervals) is considered valid. In choosing prior probabilities for parameters, we followed Kéry and Royle (2021)'s example, using largely non-informative priors indicating a lack of initial knowledge about the parameter values.

Data processing

The data underlying our model come from surveys run by the Marine Protected Area (MPA) Watch program. Each surveyor walks a pre-set transect along the coastline, logging the activities

[1]Chapter 4, section 10 of Kéry, M., & Royle, J. A. (2021). Applied hierarchical modeling in ecology—Modeling distribution, abundance and species richness using R and BUGS. Volume 2: Dynamic and Advanced Models.

they observe people engaging in on a standardized datasheet. We assume that there are no false positives e.g. if a surveyor observed a kayaker, there was a kayaker there. Surveyors report on all categories as present or explicitly absent (as far as they can observe) in each survey. Detailed activities from the surveys have been grouped into the following larger categories (see Appendix A for the complete list): animals (e.g. visitors walking their dogs), onshore recreation (sandy or rocky activities, not including tidepooling), offshore recreation (swimming, snorkeling, SCUBA diving, surfing, kiteboarding, and other board sports), onshore fishing (shore-based trap, net, or spear fishing), offshore fishing (fishing from a boat using a variety of methods), recreational boating (diving, whale watching and other non-fishing boats), tidepooling, and potential violations of MPA rules. Transects have been set up for both MPA sites throughout the length of California's coast, as well as non-MPA sites, to allow explicit comparisons between locations that have been designated as protected versus those that have not. These non-MPA sites are not all chosen to deliberately contrast with specific MPAs, so our analysis does not rely on paired tests and instead treats them as two separate groups of sites (MPAs and non-MPAs).

GreenInfoNetwork (GIN) staff process the raw survey data using the following strategy: On a given day d of the year t, for a given transect j (within an MPA/non-MPA site i), if a surveyor saw someone doing an activity in any of the subcategories that are assigned to, for example, "Onshore recreation," we consider that activity "present." GIN staff report the number of surveys on that day of that year for that transect, $n_{i,j,t,d}$, and they count how many of those surveys had that activity present, $y_{i,j,t,d}$, up to the number of surveys for that day of that year (Figure 1).

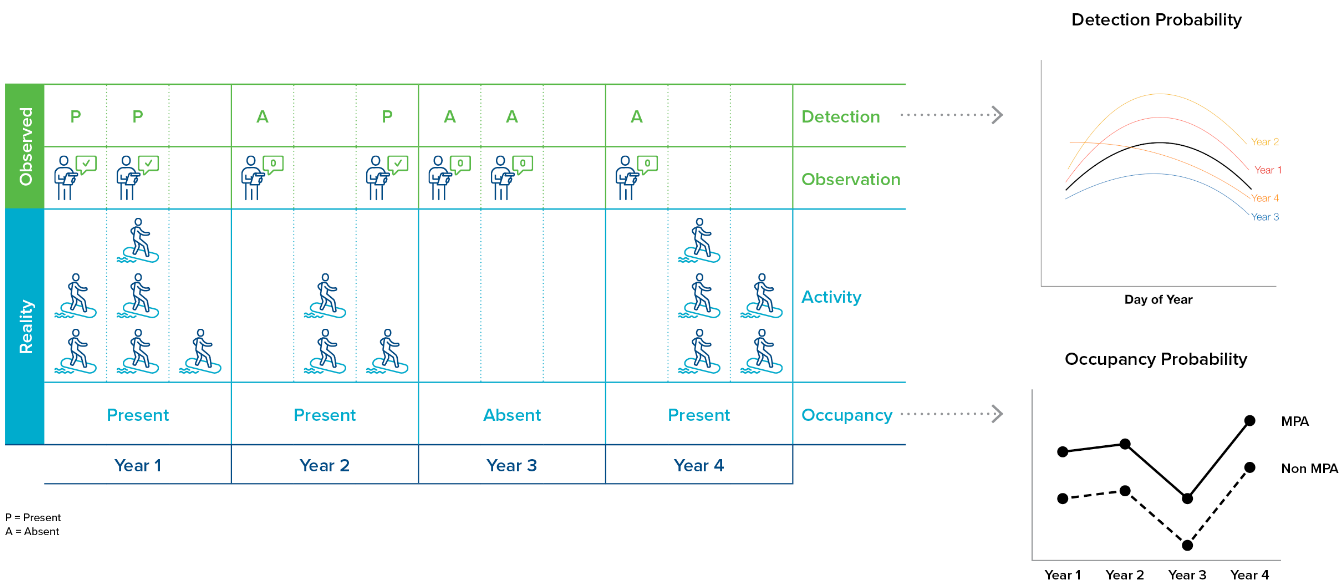
We model this process for each transect over the course of a year, in order to have enough repeated measurements of that transect to estimate the detection probability. This is because we must have some cases in which activities were detected by some observers and not others, so that we may extrapolate across locations with no observations to determine where activities might have taken place. We use occupancy rather than abundance for pragmatic reasons, given that there could be non-independence at the transect level (e.g. groups of people walking dogs together versus as individuals). In addition, some transects are longer than others, and some surveys were shore-based while others were boat-based, so we account for unmeasured transect-level variation as a random effect. Also, by aggregating activity categories, we avoid the difficulty with fine classifications of different activities that may vary in different parts of California. We do note that this level of aggregation/summarization results in a high level of 'present' measurements for most activities in most years.

Model structure

Note that each activity category is modeled separately. We used the same model structure for each activity, with the exception of a slightly different prior on one parameter for onshore recreation. We describe the model below, and note where onshore recreation differs.

Detection probability depends on 1) a baseline detection probability, p_{base}, 2) a quadratic function of the day of the year (Julian date divided by 30) d with coefficients $\beta_{\text{lin},t}$ and $\beta_{\text{quad},t}$ (both random effects with different values for different years, essentially an interaction with the year), 3) an additive random effect centered at zero for each year's impact on detection, ϵ_t, and 4) an additive random effect centered at zero for the individual transect's identity, $\epsilon_{j,t}$. (The standard deviation for the transect random effects is allowed to differ from year to year, hence the dependence on t; this follows Kéry and Royle (2021)'s example.) The quadratic function of d accounts for the potentially higher sampling effort in summer (and higher numbers of actual visitors in summer). The transect random effect accounts for variation from one transect to the next, possibly due to

Figure 1: **Schematic of the observation process and how it translates to occurrence and detection probability estimates in the model.** Occupancy modeling accounts for imperfect detection by using multiple observations of the same event at the same location to calculate the probability of accurately detecting that event (e.g. multiple surveys in a given year, in which observers and activities may or may not overlap). The model simultaneously applies that detection probability to all the other locations and times where there are only single (or no) observations. The method also accounts for uneven sampling, allowing us to draw statistically strong conclusions about actual occupancy (coastal use) despite a messy dataset.



better coastal access through parking or other amenities, due to the coastline type (bluffs may be less accessible than beaches), or simply word-of-mouth from volunteers who might be more aware of some transects than others.

The probability of detection, $p_{j,t}(d)$ is itself restricted between 0 and 1, via a logit link function. The other variables and their coefficients are allowed to vary from negative to positive infinity as is typical for regression parameters. The data are related to the probability of detection via a binomial distribution, where $n_{i,j,t,d}$ is the number of surveys for that transect and day of the year (in the data, this ranges from 1 to 25). The probability of occupancy (use of a site for a particular activity, $z_{i,t}$) is defined at the MPA/non-MPA site level, i.

$$
\begin{aligned}
& y_{i,j,t,d} \sim \text{Binomial}\left(z_{i,t} \cdot p_{j,t}(d),\ n_{i,j,t,d}\right) \\
\text{where} \quad & \text{logit}\left(p_{j,t}(d)\right) = p_{\text{base}} + \beta_{\text{lin},t} \cdot d + \beta_{\text{quad},t} \cdot d^2 + \epsilon_t + \epsilon_{j,t} \\
\text{and} \quad & i \text{ is the site} \\
& j \text{ is the transect (within site)} \\
& t \text{ is the year (2012–2020)} \\
& d \text{ is the Julian date divided by 30}
\end{aligned}
$$

The use of the binomial distribution for a set of surveys with the same covariates follows Kéry and Royle (2021). Random effects for detection are Gaussian-distributed, and the linear and quadratic interactions with time are allowed to have both a μ and σ:

$$
\begin{aligned}
\epsilon_t &\sim \mathcal{N}(0, \sigma_{\text{yearDet}}) \\
\epsilon_{j,t} &\sim \mathcal{N}(0, \sigma_{\text{tsect},t}) \\
\beta_{\text{lin},t} &\sim \mathcal{N}(\mu_{\text{lin}}, \sigma_{\text{lin}}) \\
\beta_{\text{quad},t} &\sim \mathcal{N}(\mu_{\text{quad}}, \sigma_{\text{quad}})
\end{aligned}
$$

The occupancy of the site in a given year $z_{i,t}$ is Bernoulli-distributed with probability $\psi_{i,t}$. This probability is also related to its predictors via a logit link function. The predictors of occupancy are 1) an overall mean or baseline value for occupancy in MPAs, β_{MPA}, multiplied by an indicator variable x_{MPA} (1 for sites that are MPAs and 0 otherwise), 2) a separate mean or baseline value for non-MPA sites, $\beta_{\text{non-MPA}}$ multiplied by $1 - x_{\text{MPA}}$, 3) an additive random effect centered at zero for each year's impact on occupancy, δ_t, 4) an additive random effect centered at zero for the variation between each MPA/non-MPA site in addition to the difference due to its MPA/non-MPA status, δ_i, and 5) a linear slope effect of population density, β_{popden}.[2]

$$
\begin{aligned}
& z_{i,t} \sim \text{Bernoulli}\left(\psi_{i,t}\right) \\
\text{where} \quad & \text{logit}\left(\psi_{i,t}\right) = \beta_{\text{MPA}} \cdot x_{\text{MPA}} + \beta_{\text{non-MPA}} \cdot (1 - x_{\text{MPA}}) + \beta_{\text{popden}} \cdot x_{\text{popden}} + \delta_t + \delta_i
\end{aligned}
$$

We chose to parameterize the MPA effect as two separate means in order to ensure that we could make both of their priors flat on the probability scale (see below for more on priors). To check whether the MPA status of a site affected its occupancy probability, we calculated the difference

[2] We used the U.S. Census Bureau's American Community Survey 5-year data to calculate the mean population density in census tracts adjacent to each MPA and non-MPA site over 2012-2019.

between them, $\beta_{\text{MPAdiff}} = \beta_{\text{MPA}} - \beta_{\text{non-MPA}}$, directly from the posterior samples. Also, note that x_{popden} (population density) is a continuous variable, so we centered and scaled it. Centering allowed our baseline probabilities to be interpreted as corresponding to mean values of population density, and scaling would have allowed comparison of the magnitude of effects of different covariates if we had other covariate predictors. Because x_{popden} is a continuous variable, β_{popden} is a linear slope coefficient. Random effects for occupancy are Gaussian-distributed:

$$\delta_t \sim \mathcal{N}(0, \sigma_{\text{yearOcc}})$$
$$\delta_i \sim \mathcal{N}(0, \sigma_{\text{site}})$$

Our prior distributions for model parameters are largely non-informative, representing our lack of previous knowledge about these factors. These take the form of: 1) Gaussian distributions with very wide standard deviations for parameters that can vary from negative infinity to positive infinity, i.e. $\beta_{\text{popden}} \sim \mathcal{N}(0, 1000)$; 2) uniform distributions between 0 and 1 for parameters on the probability scale, i.e. $\text{logit}(p_{\text{base}}) \sim \text{Uniform}(0, 1)$, $\text{logit}(\beta_{\text{MPA}}) \sim \text{Uniform}(0, 1)$ and $\text{logit}(\beta_{\text{non-MPA}}) \sim \text{Uniform}(0, 1)$; 3) half-Cauchy distributions for our standard deviations, i.e. σ_{site}, $\sigma_{\text{tsect},t}$ and σ_{yearOcc}, σ_{yearDet}, σ_{lin}, and σ_{quad}). We do not expect very high standard deviations, so the Cauchy distribution is a good choice, with higher weight at smaller values and heavy tails, allowing large values. That said, we used Gelman (2006)'s recommendation of a slightly less-informative Cauchy prior with mean zero and scale 2.5.[3] See below in "alternative modeling choices" for notes on the lack of sensitivity to the choice of priors, lending confidence to the use of half-Cauchy priors which aided convergence without unduly influencing posteriors.

Visual assessment of mixing and Gelman-Rubin statistics for nearly all parameters in all models indicated convergence: all tracked parameters had $\hat{R} < 1.1$ and visually demonstrated good mixing, though some required longer MCMC runs than others in order to achieve this. The exception was onshore recreation, for which we had to use a partially informative prior for σ_{yearOcc}. All other standard deviations were half-Cauchy distributed, as above, but for the year occupancy standard deviation we used $\sigma_{\text{yearOcc}} \sim \text{Uniform}(0.001, 3)$. This limit prevents runaway behavior and improves convergence, and is not unreasonable given that 3 is a fairly large standard deviation for a standardized model, especially when we have reason to believe that there is little year-to-year variation in occupancy. (see Figure 2 for a comparison of different restrictive priors for this parameter for onshore recreation.) With this restriction, we had only five parameters with $\hat{R}$ values as high as 1.148. Because these values are close to the threshold, and visual checking of those MCMC chains indicated that the mixing was adequate, we consider the model to have converged.

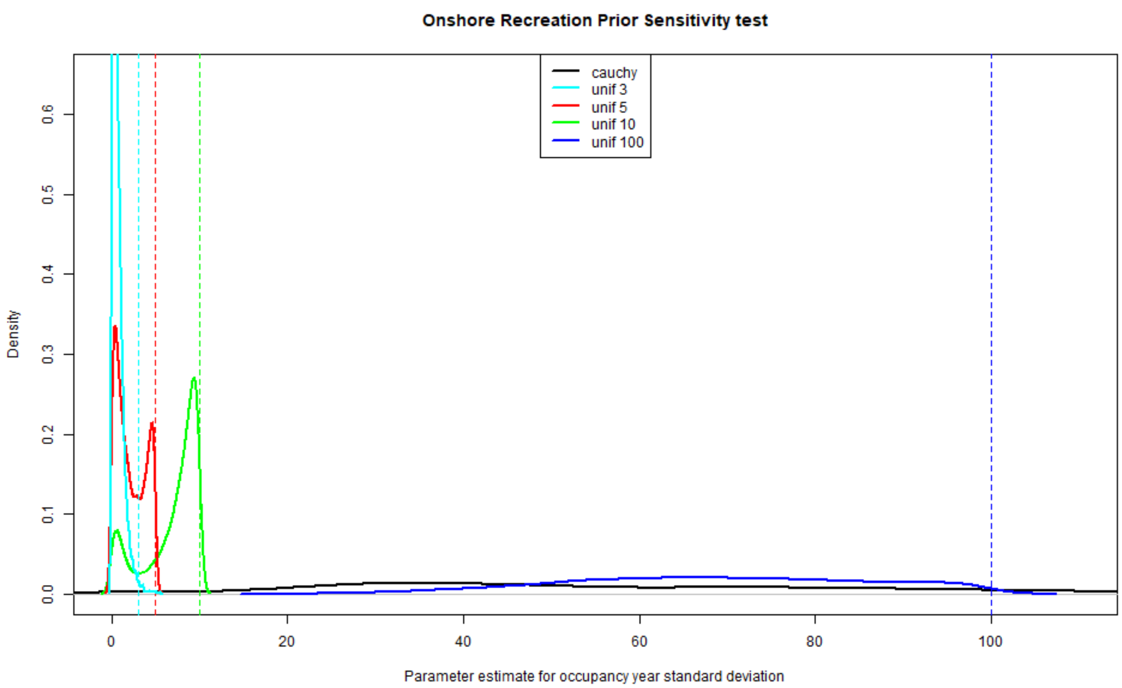
Alternative modeling choices

We considered a dynamic occupancy model which accounts for both a probability of persisting from one year to the next (ϕ) and a separate probability of newly colonizing/occupying a site that had been unoccupied (γ), and also an auto-regressive model in which the state in the previous year is included as a covariate ($z_i(t-1)$) with a coefficient $\beta_{occupied}$, but neither of these models produced better convergence behavior nor did they provide substantially different results from our chosen models for activity categories that did converge. In particular, ϕ was often 1 and γ was often 0 for individual site effects.

We also tried less-informative priors for some of the standard deviations, including uniform distributions with several different ranges, including running from 0 to 10 as in Kéry and Royle (2021),

[3] Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y. S. (2008). A weakly informative default prior distribution for logistic and other regression models. The annals of applied statistics, 2(4), 1360-1383.

Figure 2: **Investigating convergence behavior and prior sensitivity for $\sigma_{\mathbf{yearOcc}}$ for Onshore Recreation.** The half-Cauchy prior allows the MCMC sampler to choose higher and higher values for the year standard deviation for occupancy (long, flat, low, black line) – this also causes the site occupancy standard deviation to rise as the two parameters push each other larger so that the variation in both can balance out what is actually an underdetermined parameter, due to onshore recreation's low number of absences ("0"s). Restricting the bounds of the prior prevents convergence issues, and the behavior of the parameter 'trying' to get as large as possible does not occur when the parameter is restricted to the range (0,3). Three is still a somewhat large standard deviation on a standardized scale for a variable with few absences, so we chose this somewhat informative prior to allow the model to converge.



or from 0 to 100 as in Eitzel et al. (2013, 2015),[4] but this resulted in worse convergence behavior, and for those that did converge, there were only minute differences in parameter posteriors, so we feel the Cauchy priors are reasonable to use.

We also tried a variety of other correlation structures, for example including random effects in detection for both transects and sites or including random effects for sites in both detection and occurrence/occupancy, but many of these models did not converge.

Model code

Below is the JAGS code for specifying the model. JAGS uses precisions for Gaussian distributions rather than standard deviations, and several priors are defined as functions of other parameters, to ensure that the prior is uninformative on the desired scale.

```
model {

  # ------------------------------------------------------------
  # Detection Submodel.  p is probability of detection.
  # ------------------------------------------------------------

  # Random effects for detection: intercept, and linear/quadratic
  # terms in d (day of year, here called "date")
  # ....................................

  for (t in 1:nyears) {
    # overall detection probability for each year
    eps.p.year[t] ~ dnorm(0, tau.p.year)

    # Julian date, quadratic function of date, different for each year
    beta.p.1[t] ~ dnorm(mu.beta.p.1, tau.beta.p.1)
    beta.p.2[t] ~ dnorm(mu.beta.p.2, tau.beta.p.2)
  }

  # Priors for detection model
  # ....................................

  # baseline.p: baseline detection probability
  # uniform on probability scale
    baseline.p <- logit(mean.p)
    mean.p ~ dunif(0, 1)

  # eps.p.year: year intercept random effect
  # Note: JAGS uses precisions ('tau') for Gaussian distributions
  # We want to ensure the prior is uninformative on sd scale
```

[4] Eitzel, M. V.; Battles, J. ; York, R.; Knape, J.; de Valpine, P. (2013) Estimating Tree Growth Models from Complex Forest Monitoring Data. Ecological Applications. 23:6, 1288–1296. DOI: 10.1890/12-0504.1 (Erratum: 10.1002/eap.1424) and Eitzel, M. V.; Battles, J.; York, R.; de Valpine, P. (2015), "Can't see the trees for the forest: complex factors influence survival in a temperate second-growth forest." Ecosphere. 6:11, 1–17. DOI: 10.1890/ES15-00105.1 (Erratum: 10.1002/ecs2.1423)

```
  tau.p.year <- pow(sd.p.year, -2)
  sd.p.year ~ dt(0, pow(2.5,-2), 1)T(0,) # half-Cauchy prior

# beta.p.1: linear dependence on day-of-year
  mu.beta.p.1 ~ dnorm(0, 0.1)
  tau.beta.p.1 <- pow(sd.beta.p.1, -2)
  sd.beta.p.1 ~ dt(0, pow(2.5,-2), 1)T(0,) # half-Cauchy prior

# beta.p.2: quadratic dependence on day-of-year
  mu.beta.p.2 ~ dnorm(0, 0.1)
  tau.beta.p.2 <- pow(sd.beta.p.2, -2)
  sd.beta.p.2 ~ dt(0, pow(2.5,-2), 1)T(0,) # half-Cauchy prior

# Annually varying transect random effects in detection
# Both at the year and the transect level
  for(t in 1:nyears) {
    for(i in 1:ntransects) {
      eps.p.transect[i, t] ~ dnorm(0, tau.p.transect[t])
    }
    # the sd of transects within years can vary year-to-year
      tau.p.transect[t] <- pow(sd.p.transect[t],-2)
      sd.p.transect[t] ~ dt(0, pow(2.5,-2), 1)T(0,) # half-Cauchy prior
  }

# Actual detection model, with logit transform to include predictors
# and binomial distribution to link data to underlying occupancy and
# detection structure.  Note that this loops through obervations
# ...................................

# date[obs] is julian date (data, one per y observation)
# betas are the beta coefficients for the julian date
for (obs in 1:nobs) {
  logit(p[obs]) <-
    baseline.p +
    eps.p.year[year[obs]] +
    beta.p.1[year[obs]] * date[obs] +
    beta.p.2[year[obs]] * pow(date[obs], 2) +
    eps.p.transect[transect[obs], year[obs]]

  # The data (whether activity observed or not) are y_{ijtd}
  y[obs] ~ dbin(z[site[obs], year[obs]] * p[obs], nsurveys[obs])
}

# ------------------------------------------------------------
# Occupancy Submodel. psi is the probability of being occupied
# ------------------------------------------------------------

# Random effects for occupancy
```

```
  # ....................................

  # Site random effect
  for(si in 1:nsites) {
    eps.psi.site[si] ~ dnorm(0, tau.psi.site)
  }
  tau.psi.site <- pow(sd.psi.site, -2)
  sd.psi.site ~ dt(0, pow(2.5,-2), 1)T(0,)  # half-Cauchy prior

  # Year random effect
  for (t in 1:nyears) {
    eps.psi.year[t] ~ dnorm(0, tau.psi.year)
  }
  tau.psi.year <- pow(sd.psi.year, -2)
  sd.psi.year ~ dt(0, pow(2.5,-2), 1)T(0,)  # half-Cauchy prior

# FOR ONSHOREREC ONLY, UNIFORM DENSITY FOR SD.PSI.YEAR
# sd.psi.year ~ dunif(0.001, 3)

  # Priors
  # ....................................

  # overall mean occupancy, uniform on probability scale
    beta.psi.mpa <- logit(mean.psi.mpa)
    mean.psi.mpa ~ dunif(0, 1)
    beta.psi.nonmpa <- logit(mean.psi.nonmpa)
    mean.psi.nonmpa ~ dunif(0, 1)

  # uninformative prior on continuous scale
    beta.psi.popden ~ dnorm(0, 1.0E-6)

  # Actual occupancy model, with logit transform to include predictors
  # Note that this loops through sites and years
  # ....................................

  # eps.psi.year and eps.psi.site are random effects, and beta.psi.mpa is
  # the average occupancy of MPA sites, while beta.psi.nonmpa is the average
  # occupancy for non-MPA sites, beta.psi.popden is the population density's
  # effect on occupancy
  for (si in 1:nsites) {
    for (t in 1:nyears) {
      logit(psi[si, t]) <-
        eps.psi.year[t] + eps.psi.site[si] +
        beta.psi.nonmpa * (1 - is_mpa [si]) +
        beta.psi.mpa * is_mpa[si]+
        beta.psi.popden * popden[si]
   }
  }
```

```
  # The actual occupancy
  for (si in 1:nsites) {
    for (t in 1:nyears) {
      z[si,t] ~ dbern(psi[si,t])
    }
  }

}
```

Results

The results include two types of figures: 1) predicted figures, and 2) posterior figures. The posterior figures are largely included for transparency, while the predicted figures translate model results to the probability scale for better interpretability. Below we give the highlights of the figures.

The posterior figure showing the difference between MPA and non-MPA sites in occupancy summarizes the results for all activity categories (Figure 27). Note that MPA status has a positive impact on recboating (credible level 0.02), as well as tidepooling (credible level 0.043), while MPA status has a negative impact onshore fishing (credible level 0). Credible levels are the proportion of the posterior that lies on the other side of zero from the bulk of the posterior; 95% credible intervals from the function `HPDinterval` in R package `coda` are shown in the figures as guidelines but do not exactly correspond to the credible levels. The other activity categories have small MPA effects which strongly overlap zero, with credible levels as follows: Onshore recreation = 0.309, Offshore recreation = 0.262, Animals = 0.129, and Offshore fishing = 0.136. (Also note in the predicted figures the clear separation of the two lines in 18, and stronger overlaps in Figures 21, 3, 6, 9, 12, and 15).

Also note in the predicted figures just referenced, a general lack of variation from year-to-year in occupancy, also seen in the occupancy year standard deviation posterior figure (Figure 29; violations also has little year-to-year variation, Figure 24). The possible exception is tidepooling, which has a slightly larger posterior and Figure 3 does indeed show larger variation and a potential time trend beginning to form. With a longer time series (more years of data), perhaps variation will be better measured and trends may become apparent.

Population density posteriors show little impact of population density on occupancy for any of the activities (Figure 28), strongly overlapping zero. Credible levels were high for all activities: Tidepooling, 0.169; Animals, 0.292; Offshore Fishing, 0.366; Offshore Recreation, 0.063; Recreational Boating, 0.085; Onshore Fishing, 0.319; Violations, 0.063; Onshore Recreation, 0.25.

Site random effects on occupancy are considerable (see posterior Figure 30 and predicted Figures 19, 22, 4, 7, 10, 13, 16 and 25) – much greater than year effects, indicating a large amount of unexplained variation in all activity categories that may be fruitfully explored in future models with further covariates (including other methods of accounting for population density). Tidepooling has particularly high site variation (Figure 4), possibly because not all sites have tidepools, but most activity categories have at least some variation in sites.

Posteriors for transect random effects on detection (Figures 31 and 32) demonstrate that there is some unexplained variation in transects that shifts from year to year, larger than the year-to-year variation in occupancy, but smaller than the site-to-site variation in occupancy. This points to potential richness in modeling the detection/observation process with more detailed covariates.

Finally, the detection parameter posteriors (Figures 33, 34, 35, 36, 37, and 38) show great variation from activity to activity, which is more apparent when they are combined into predicted figures 5, 8, 17, 26, 20, 11, 23, and 14. Of particular interest are the high detection of onshore recreation (Figure 23), the strong seasonality of offshore recreation detection (Figure 14), and high detection in 2020 for animals (Figure 8).

Figure 3: **Estimated occupancy probability of tidepooling by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars overlap due to the way we calculated this estimate, the MPA effect is statistically significant. This activity category also shows the greatest change from year to year, though the overall year effect on occupancy is estimated to be small even for this category.

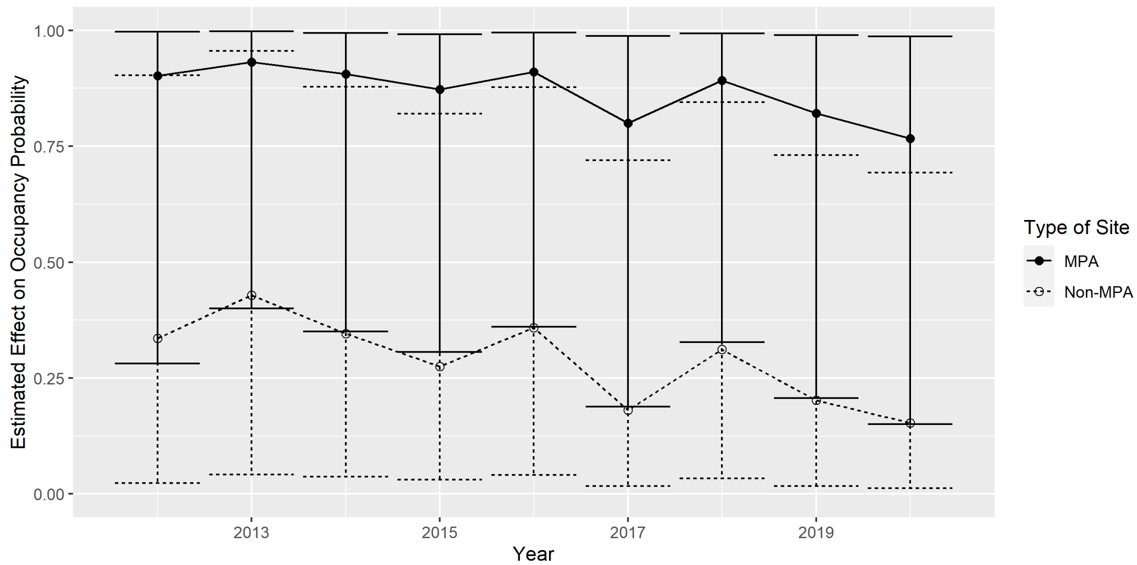


Figure 4: **Estimated occupancy probability by site on tidepooling.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site variation is statistically significant.

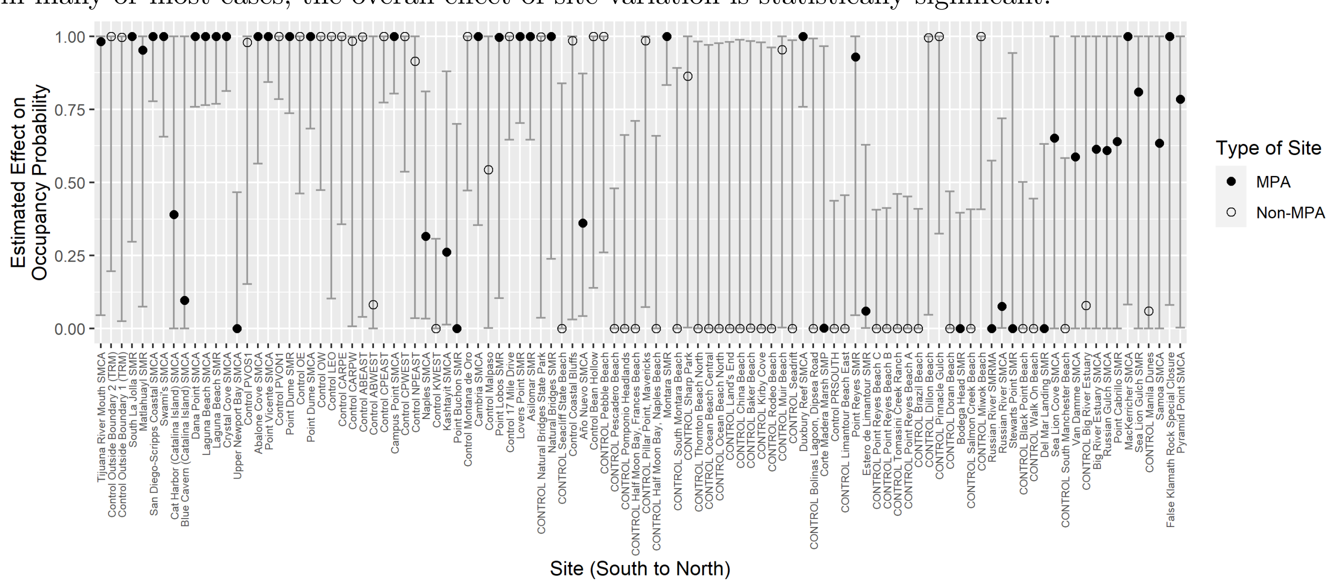


Figure 5: **Estimated detection probability for tidepooling by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

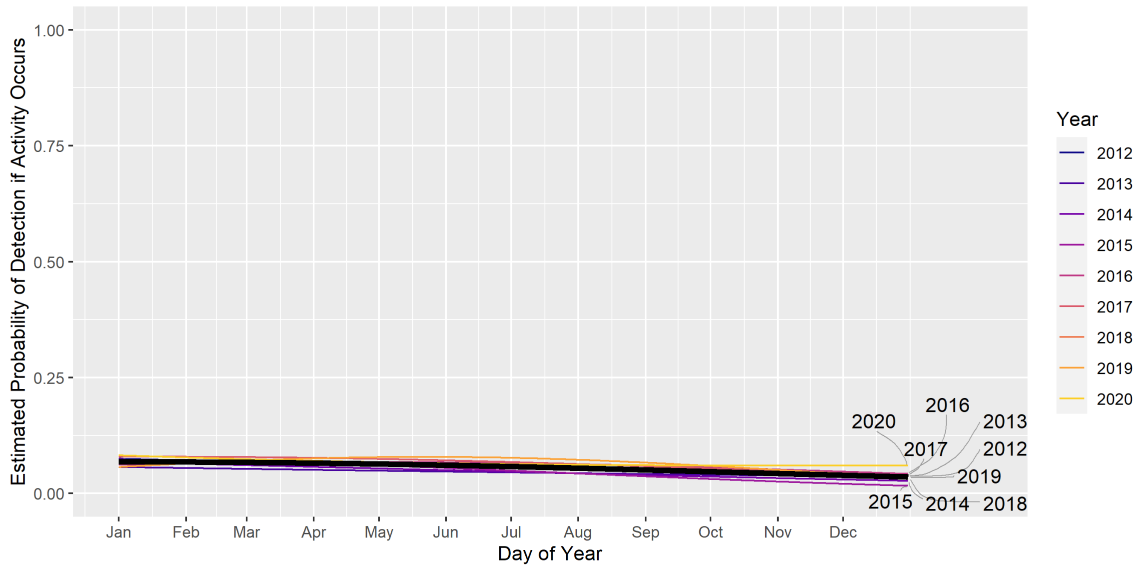


Figure 6: **Estimated occupancy probability of (domestic) "animals" by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

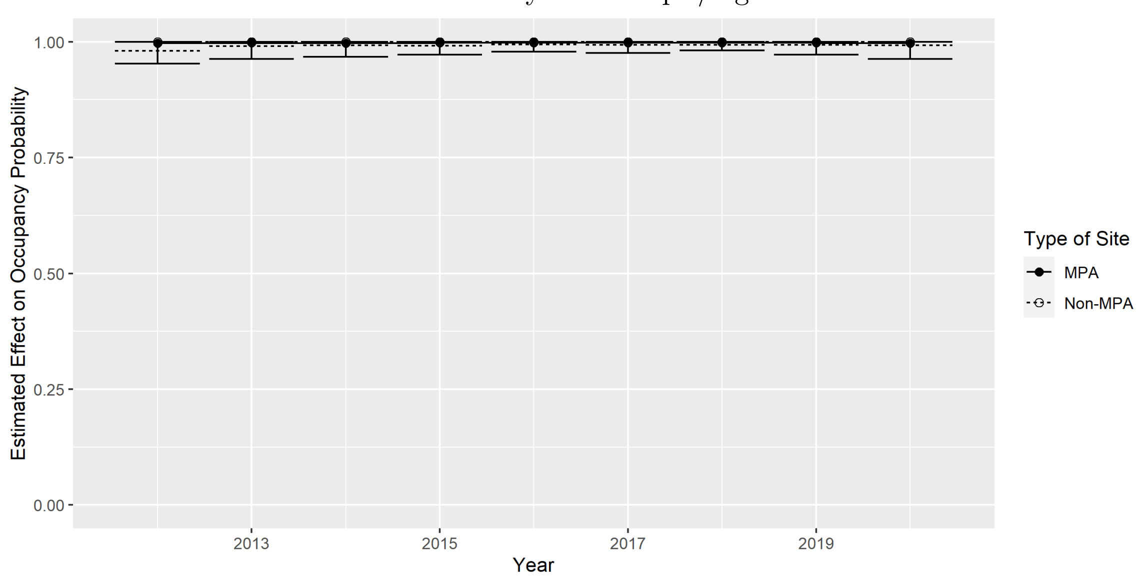


Figure 7: **Estimated occupancy probability by site on (domestic) "animals."** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site is statistically significant.

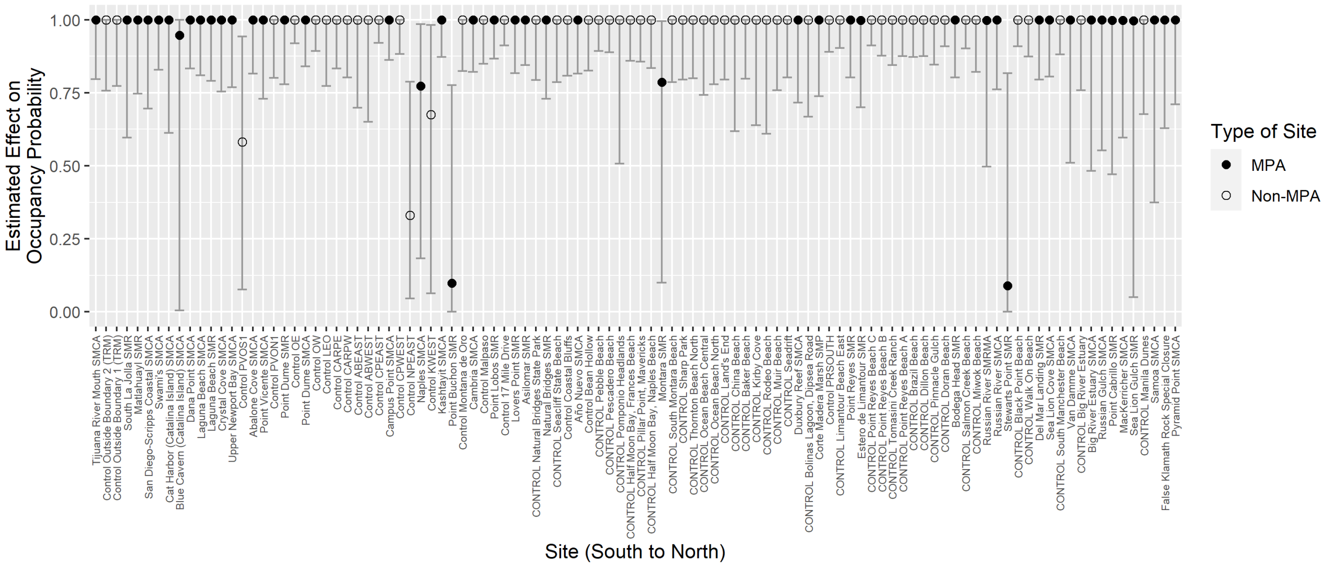


Figure 8: **Estimated detection probability for (domestic) "animals" by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

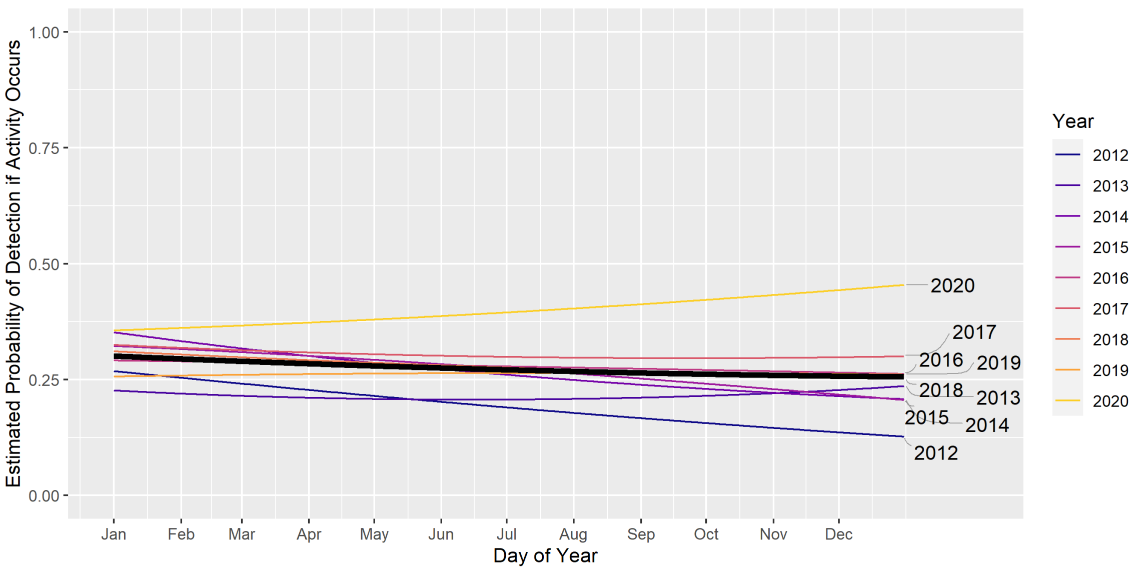


Figure 9: **Estimated occupancy probability on offshore fishing by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

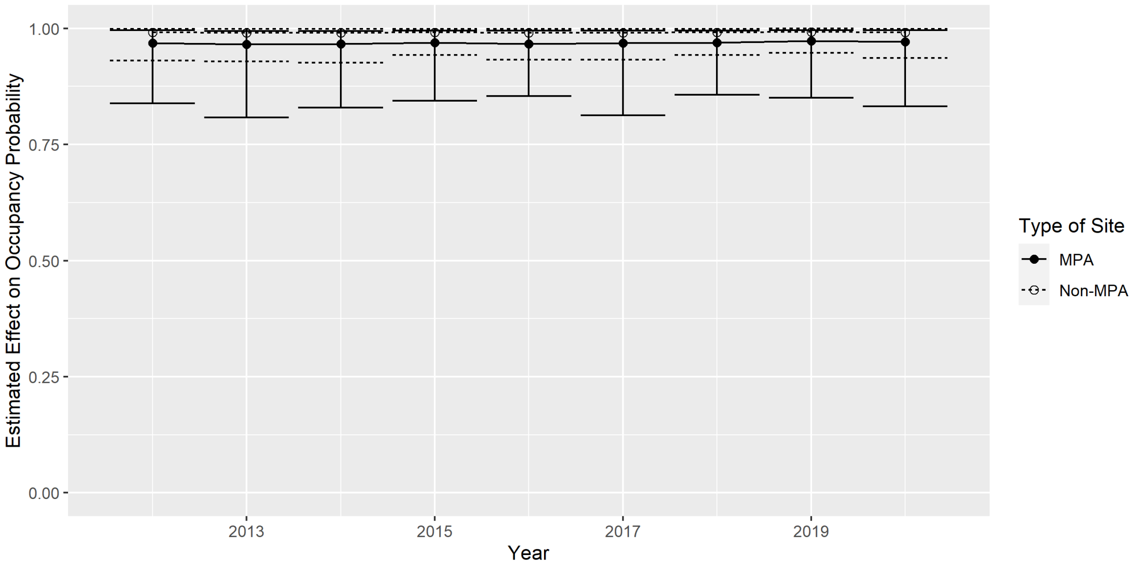


Figure 10: **Estimated occupancy probability by site on offshore fishing.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site is statistically significant.

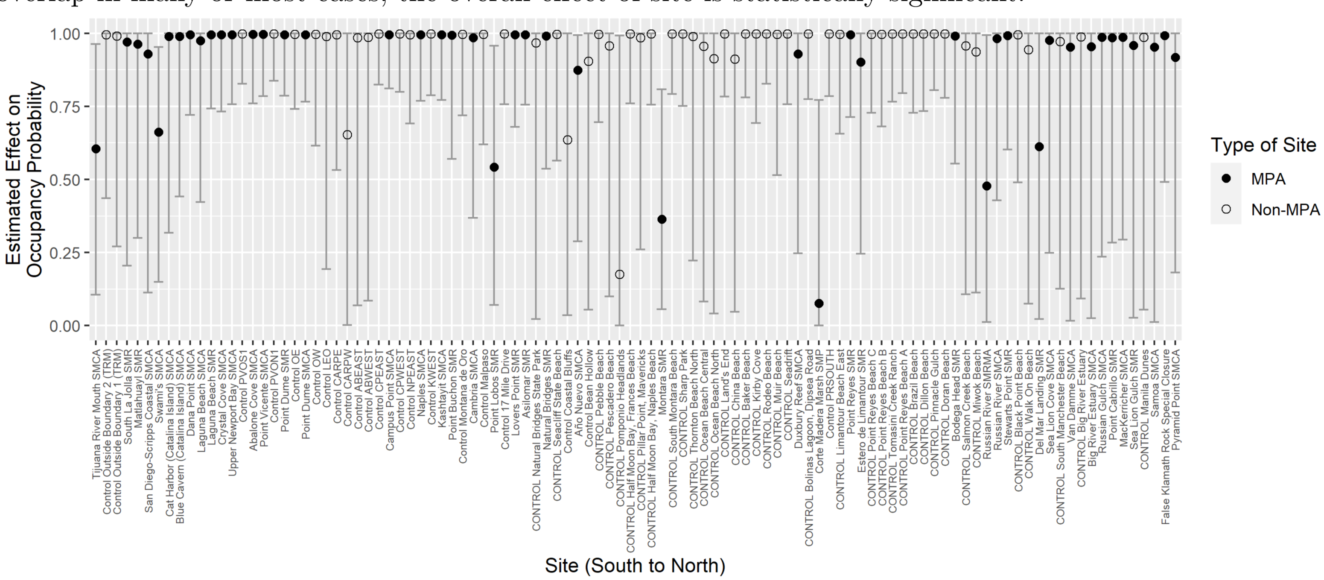


Figure 11: **Estimated detection probability for offshore fishing by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

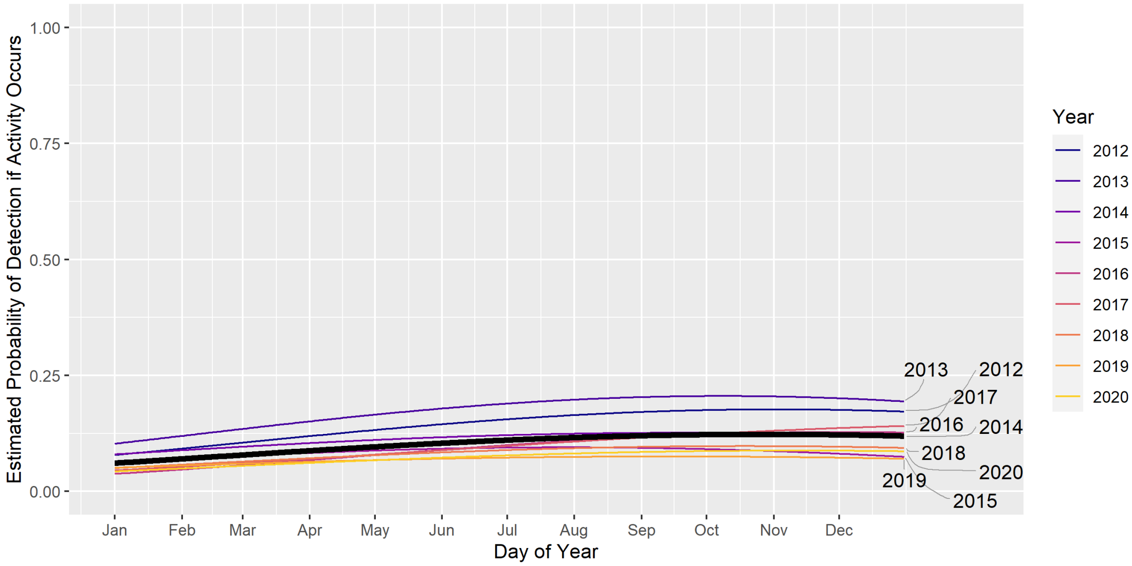


Figure 12: **Estimated occupancy probability of offshore recreation by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

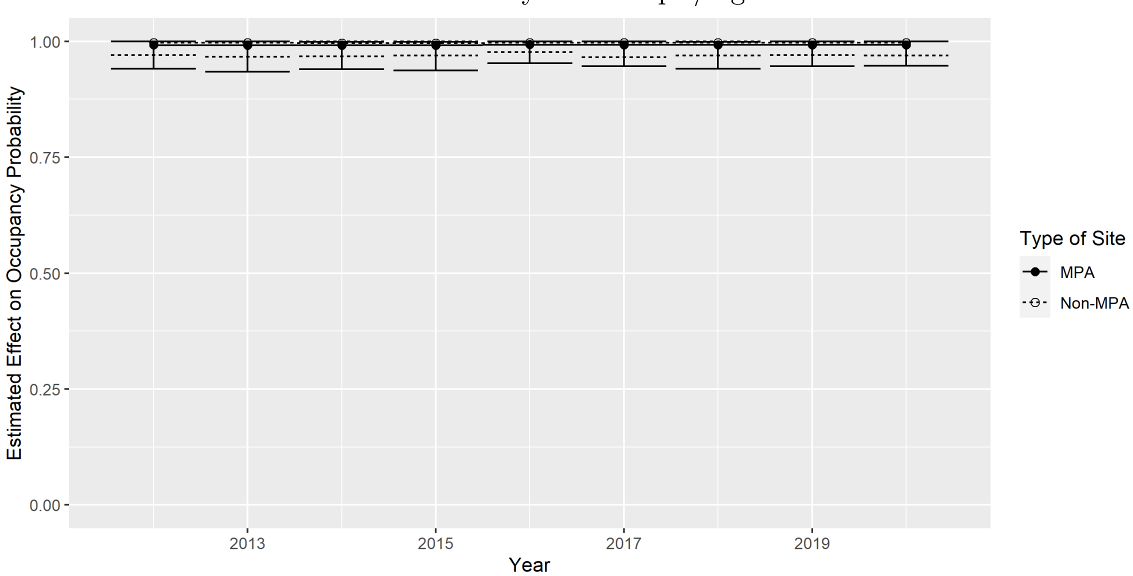


Figure 13: **Estimated occupancy probability by site on offshore recreation.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site is statistically significant.

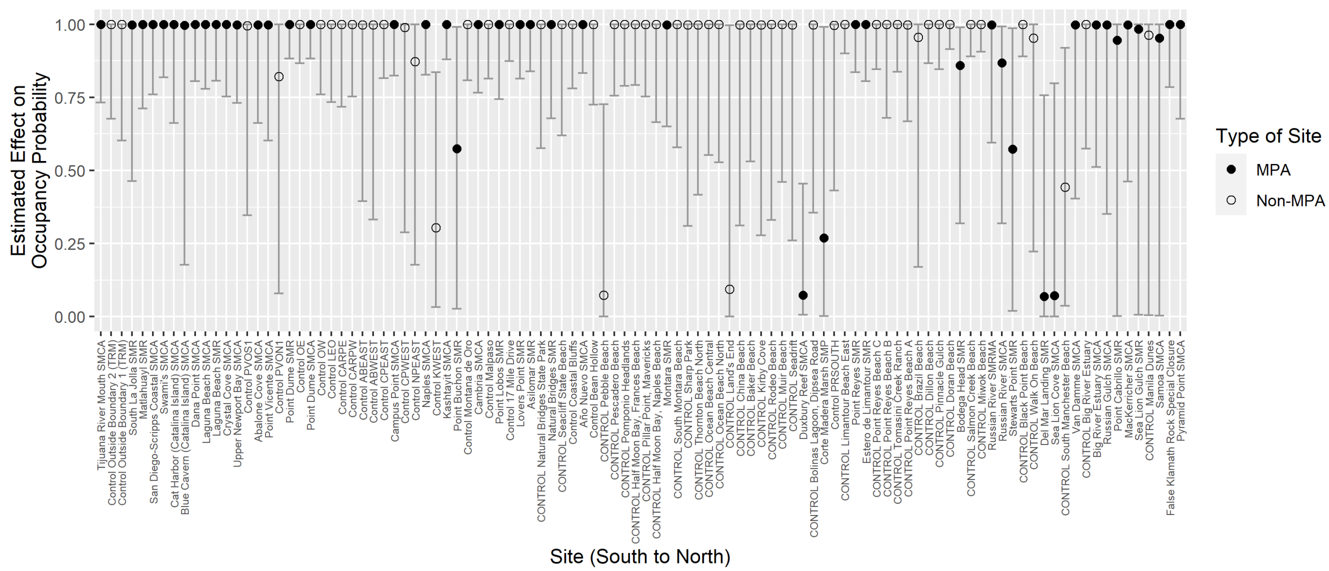


Figure 14: **Estimated detection probability of offshore recreation by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

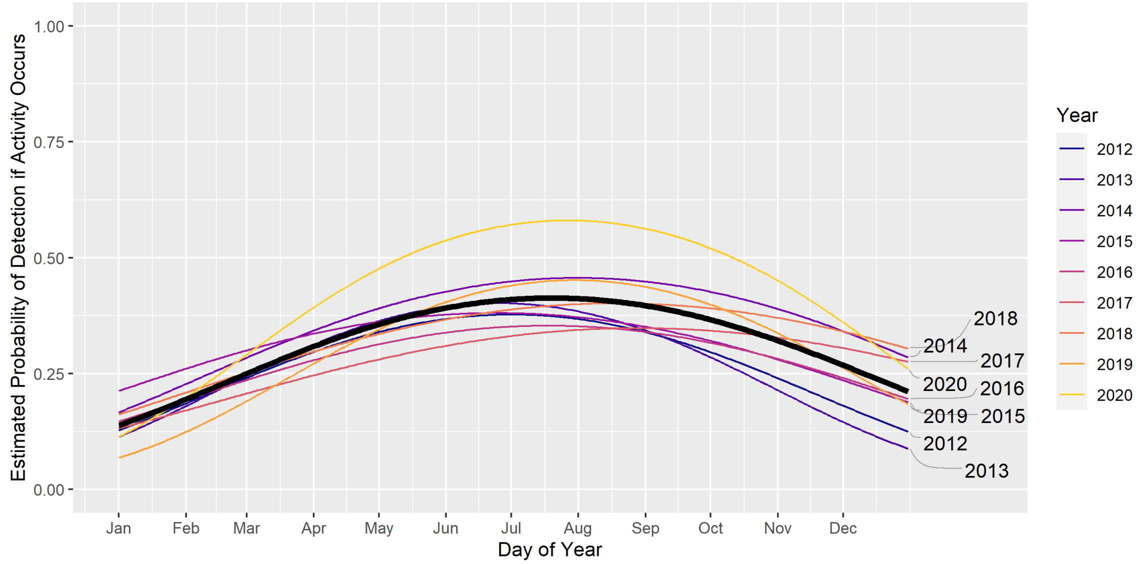


Figure 15: **Estimated occupancy probability of recreational boating by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars overlap due to the way we calculated this estimate, the MPA effect is statistically significant.

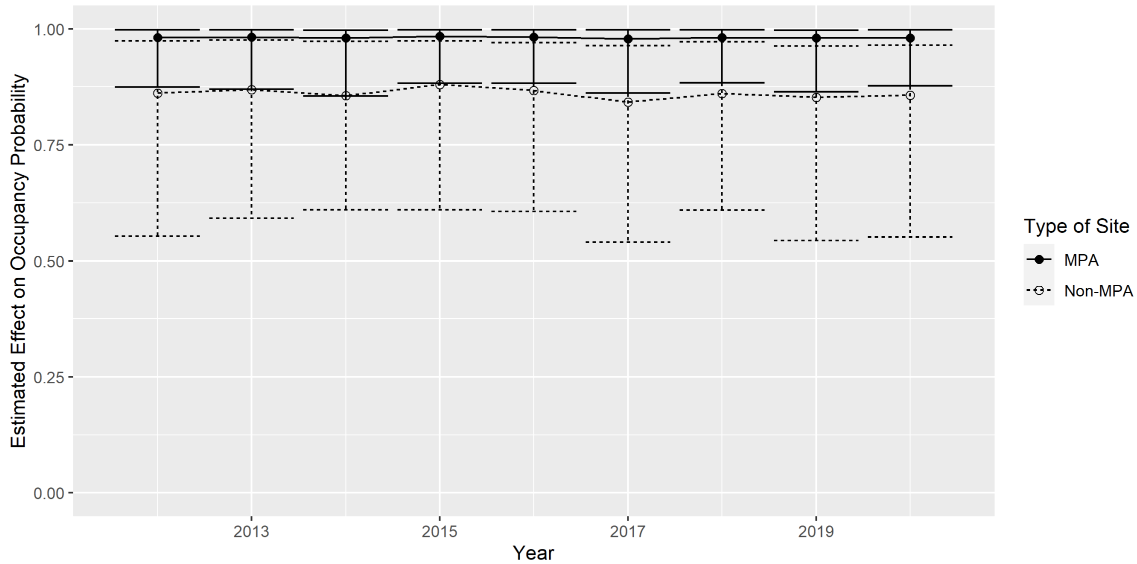


Figure 16: **Estimated occupancy probability by site on recreational boating.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site is statistically significant.

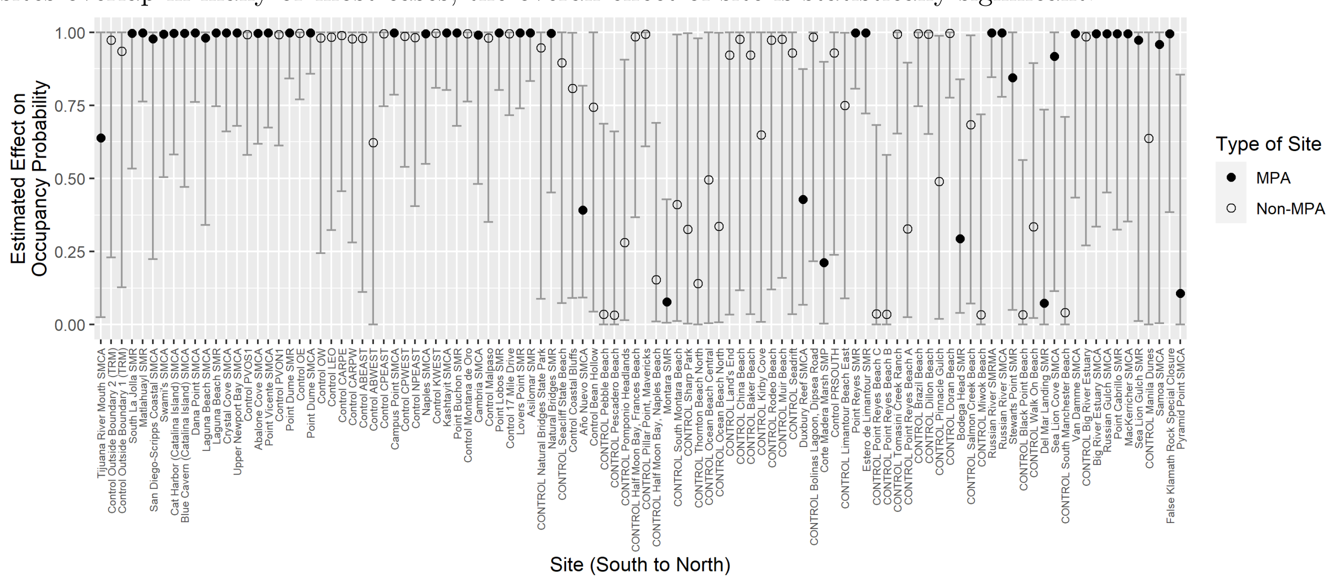


Figure 17: **Estimated detection probability of recreational boating by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

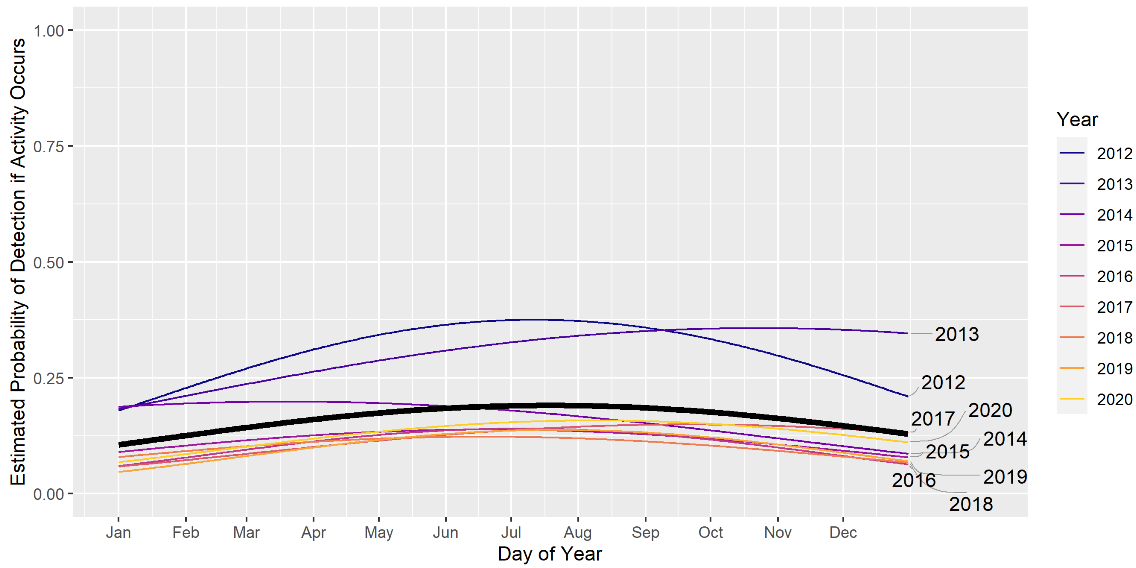


Figure 18: **Estimated occupancy probability for onshore fishing by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

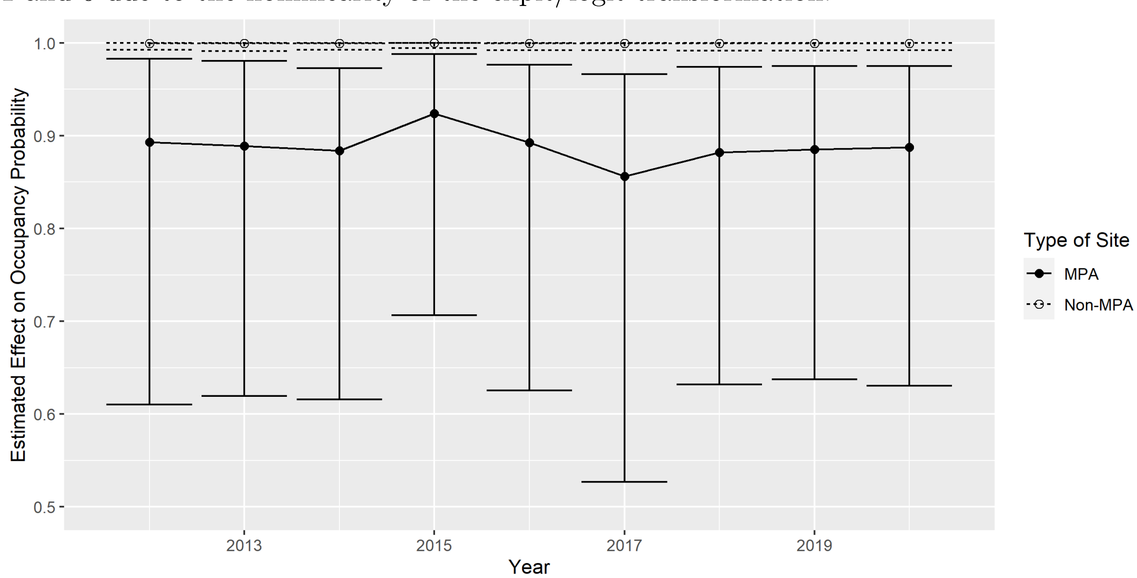


Figure 19: **Estimated occupancy probability by site on onshore fishing.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site is statistically significant.

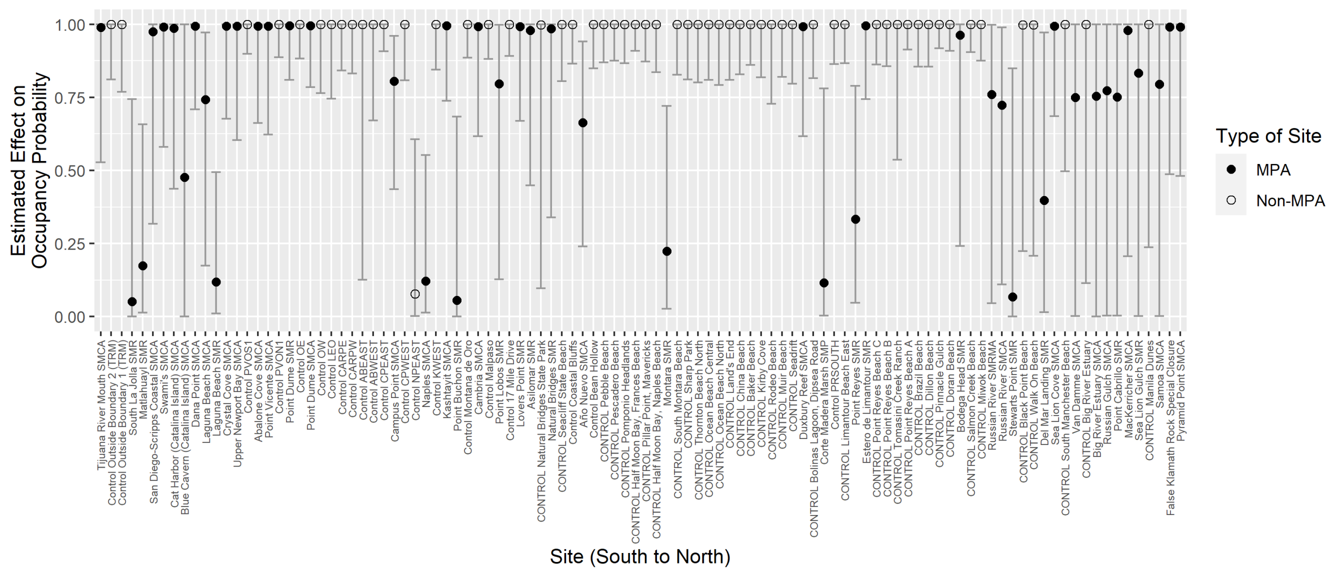


Figure 20: **Estimated detection probability of onshore fishing by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

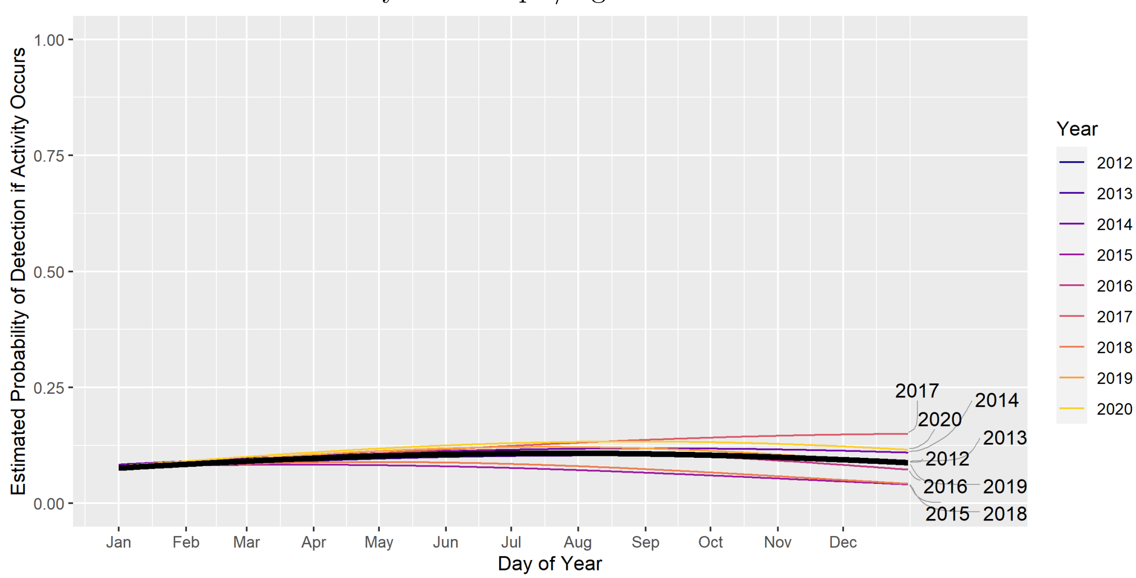


Figure 21: **Estimated occupancy probability for onshore recreation by year and MPA status.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

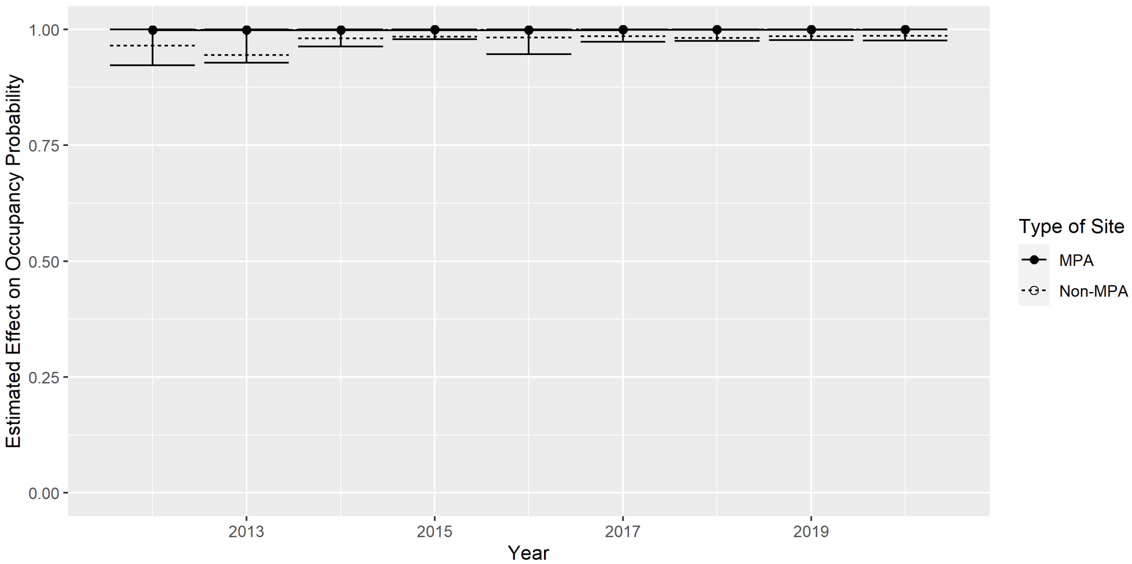


Figure 22: **Estimated occupancy probability by site on onshore recreation probability.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. The high overlap of error bars between individual sites reflects the very small estimate of the site standard deviation, shown later in Figure 30.

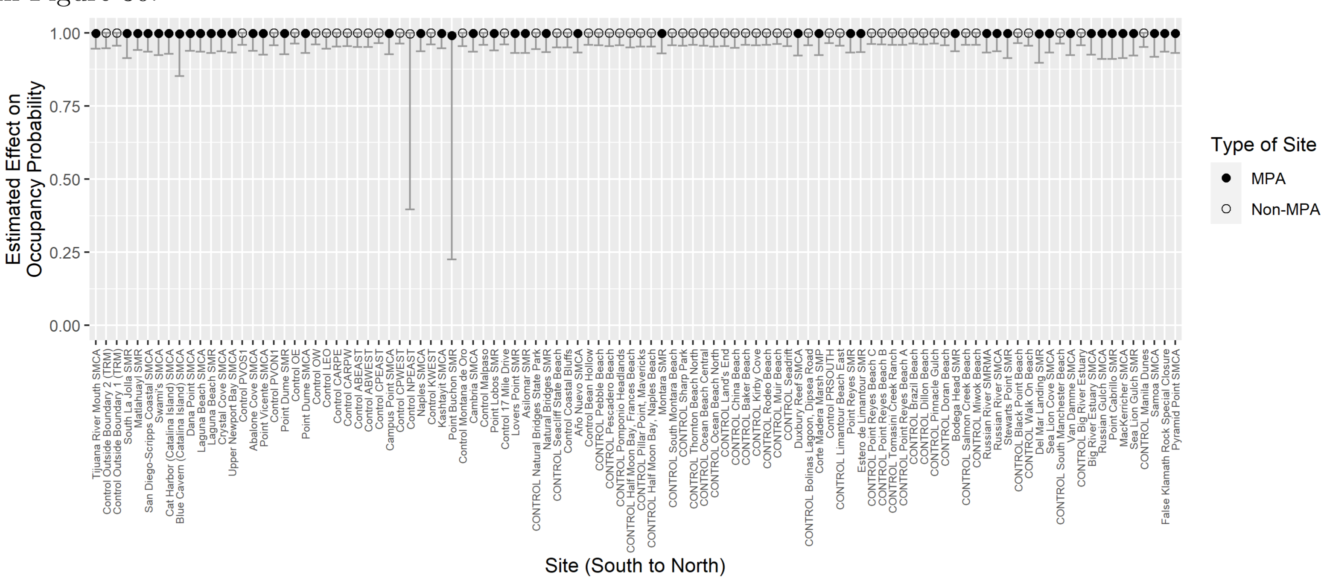


Figure 23: **Estimated detection probability of onshore recreation by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

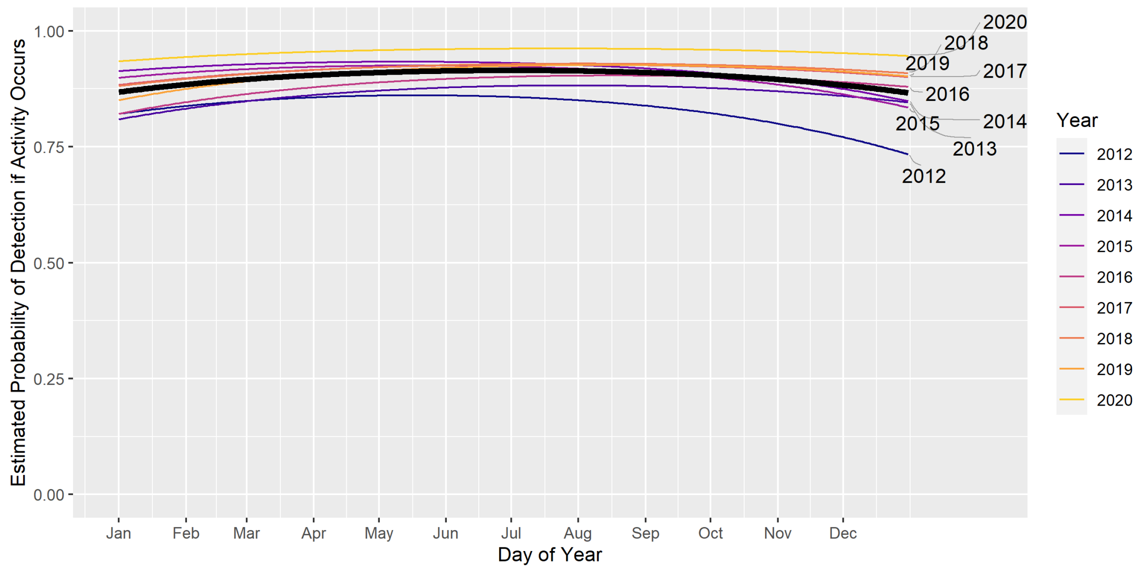


Figure 24: **Predicted occupancy probability of potential MPA violations by year.** There are no violations in non-MPA sites, by definition, so these plots only show MPAs. The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

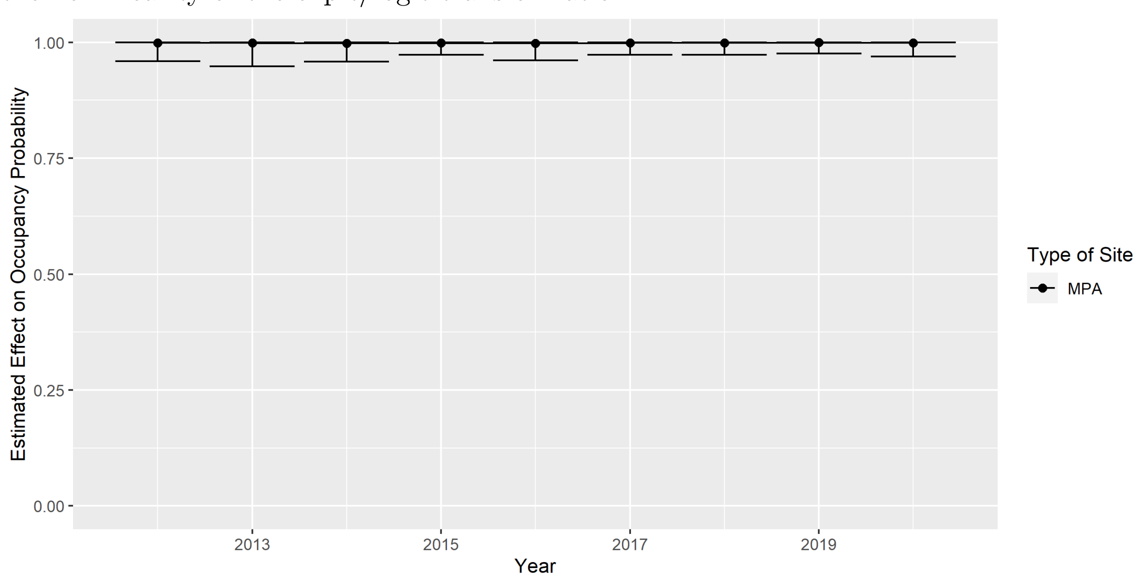


Figure 25: **Estimated occupancy probability by site on potential MPA violations.** There are no violations in non-MPA sites, by definition, so these plots only show MPAs. The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation. Though error bars between individual sites overlap in many or most cases, the overall effect of site is statistically significant.

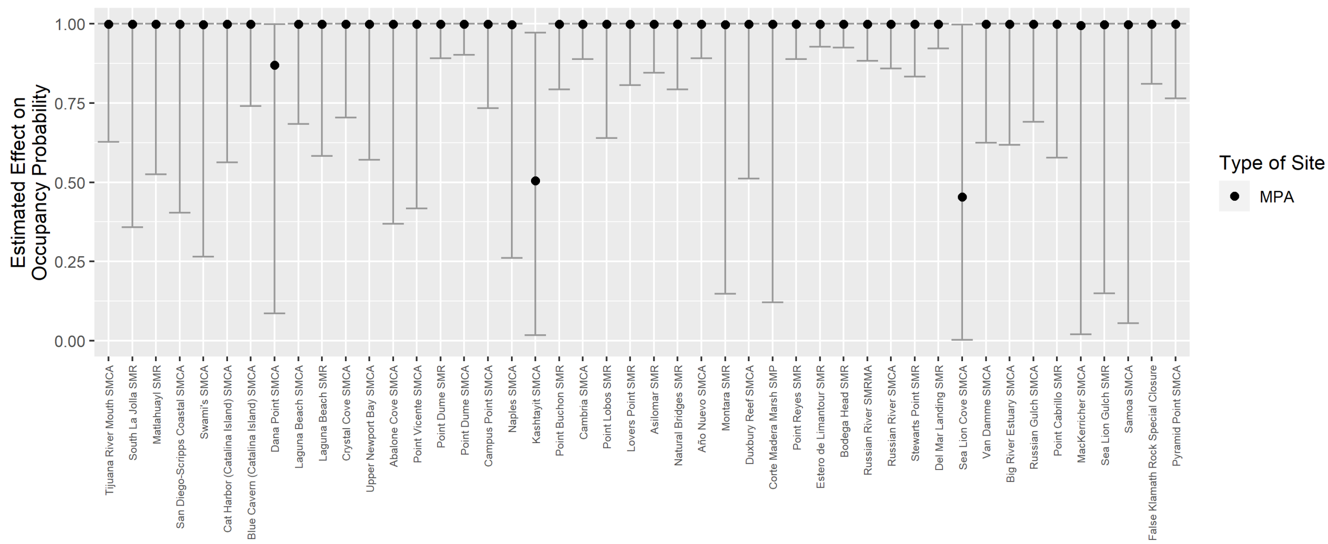


Figure 26: **Estimated detection probability of potential MPA violations by year and day of year.** The parameters have been transformed to the probability scale, so some distortion may occur near 1 and 0 due to the nonlinearity of the expit/logit transformation.

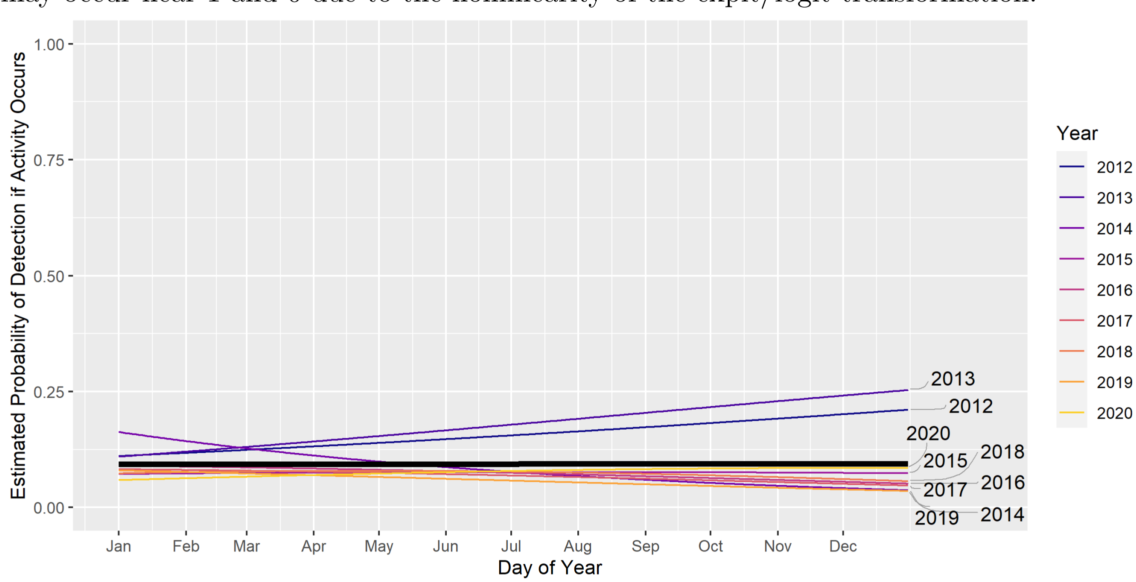


Figure 27: **Posteriors for all activities for the impact of MPA status on occupancy probability, $\beta_{\mathbf{MPAdiff}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison. For violations, where there are no non-MPA sites by definition, this parameter reflects the overall occupancy.

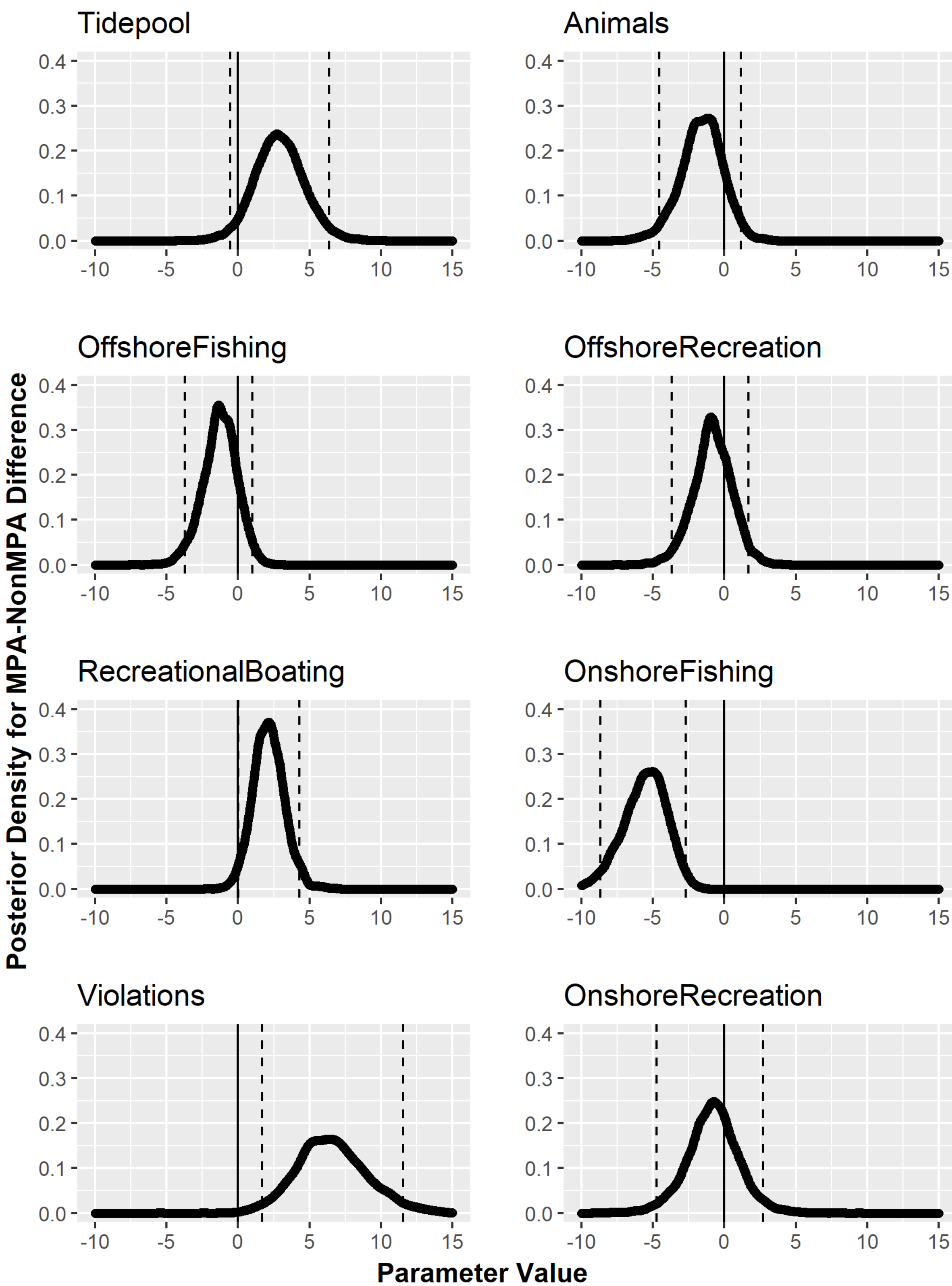


Figure 28: **Posteriors for all activities for the impact of population density on occupancy probability, $\beta_{\mathbf{popden}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

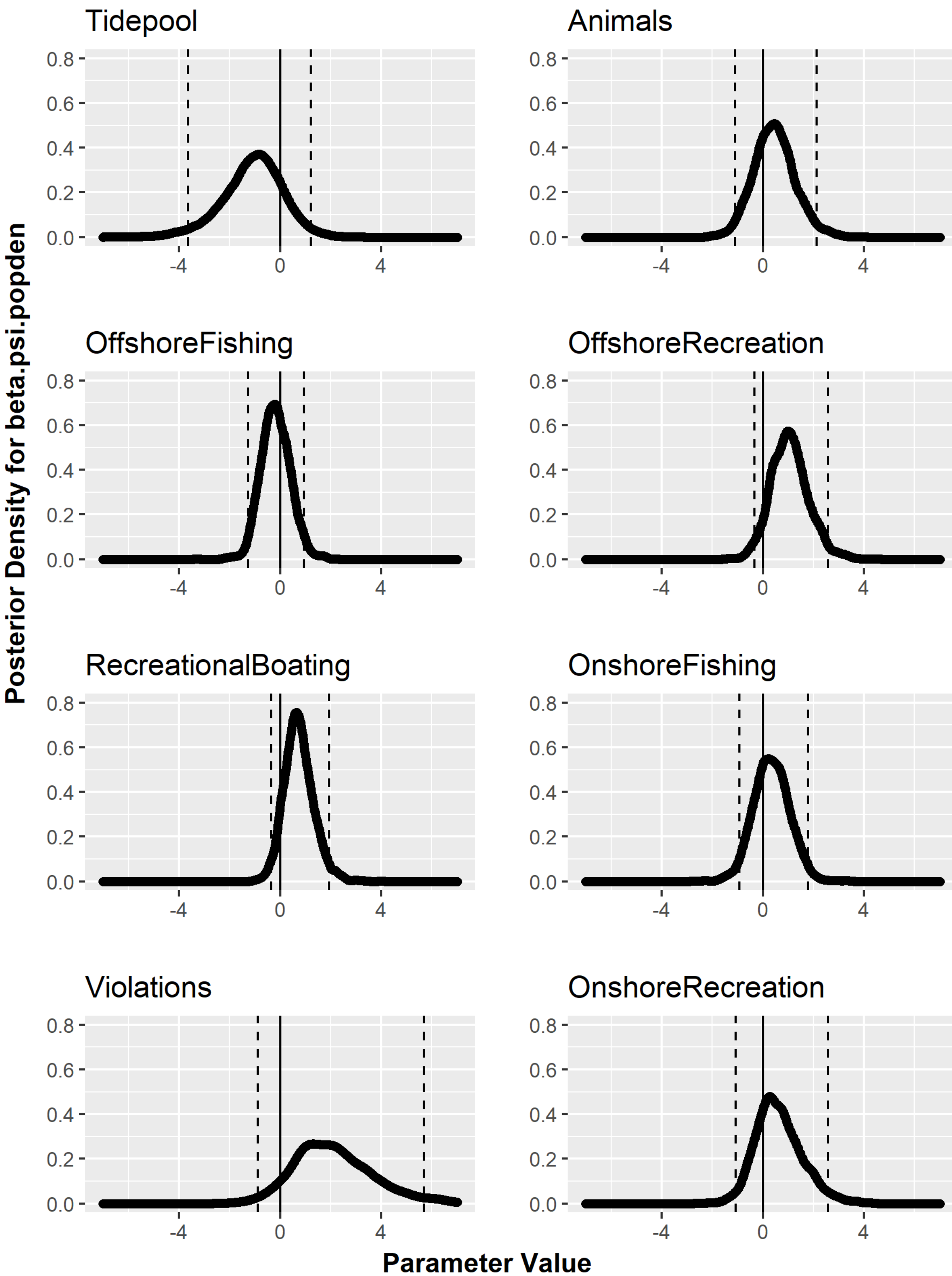


Figure 29: **Posteriors for all activities for the year random effect standard deviation on occupancy probability, $\sigma_{\mathbf{yearOcc}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

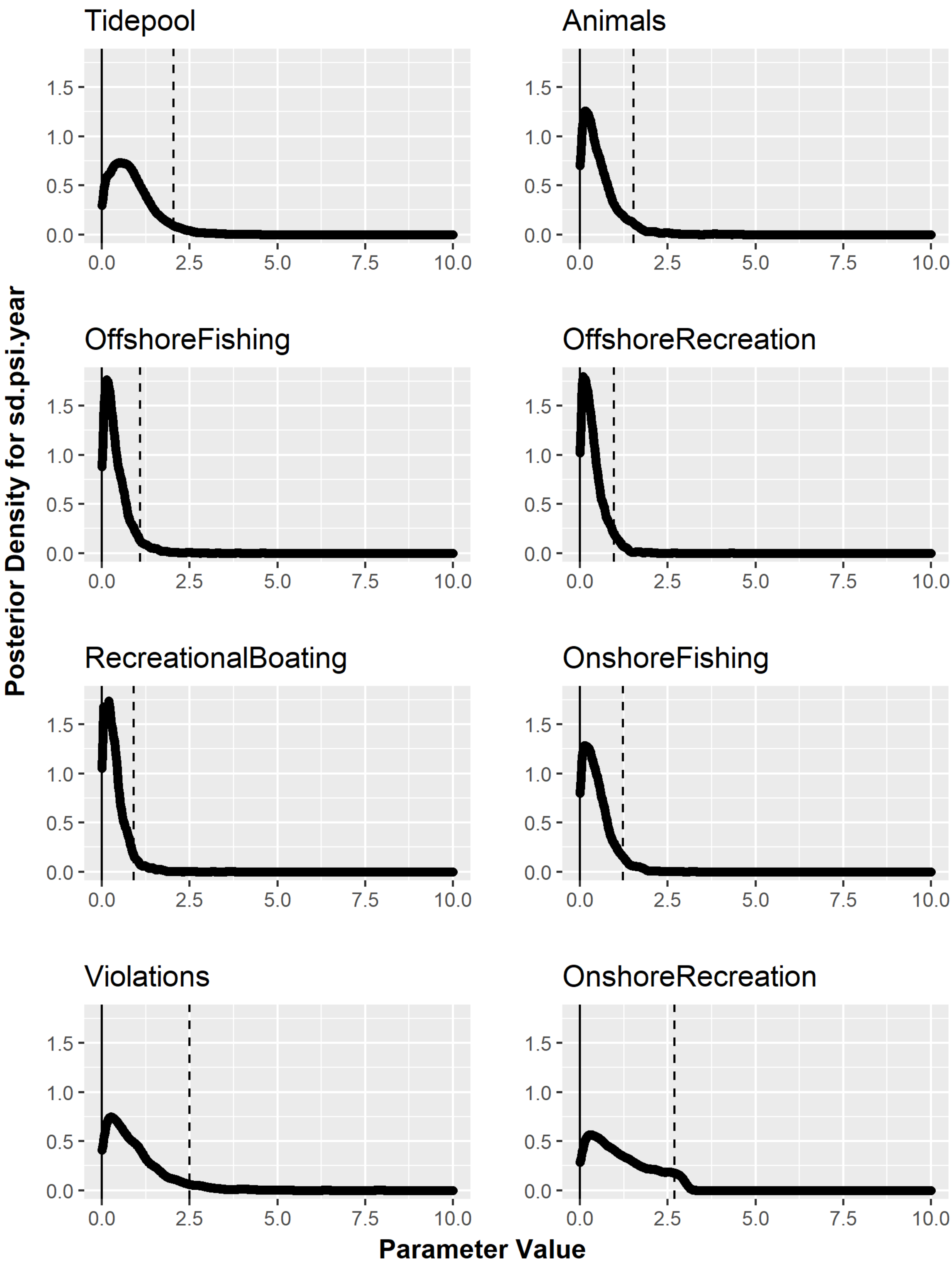


Figure 30: **Posteriors for all activities for the site random effect standard deviation on occupancy probability, $\sigma_{\mathbf{site}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

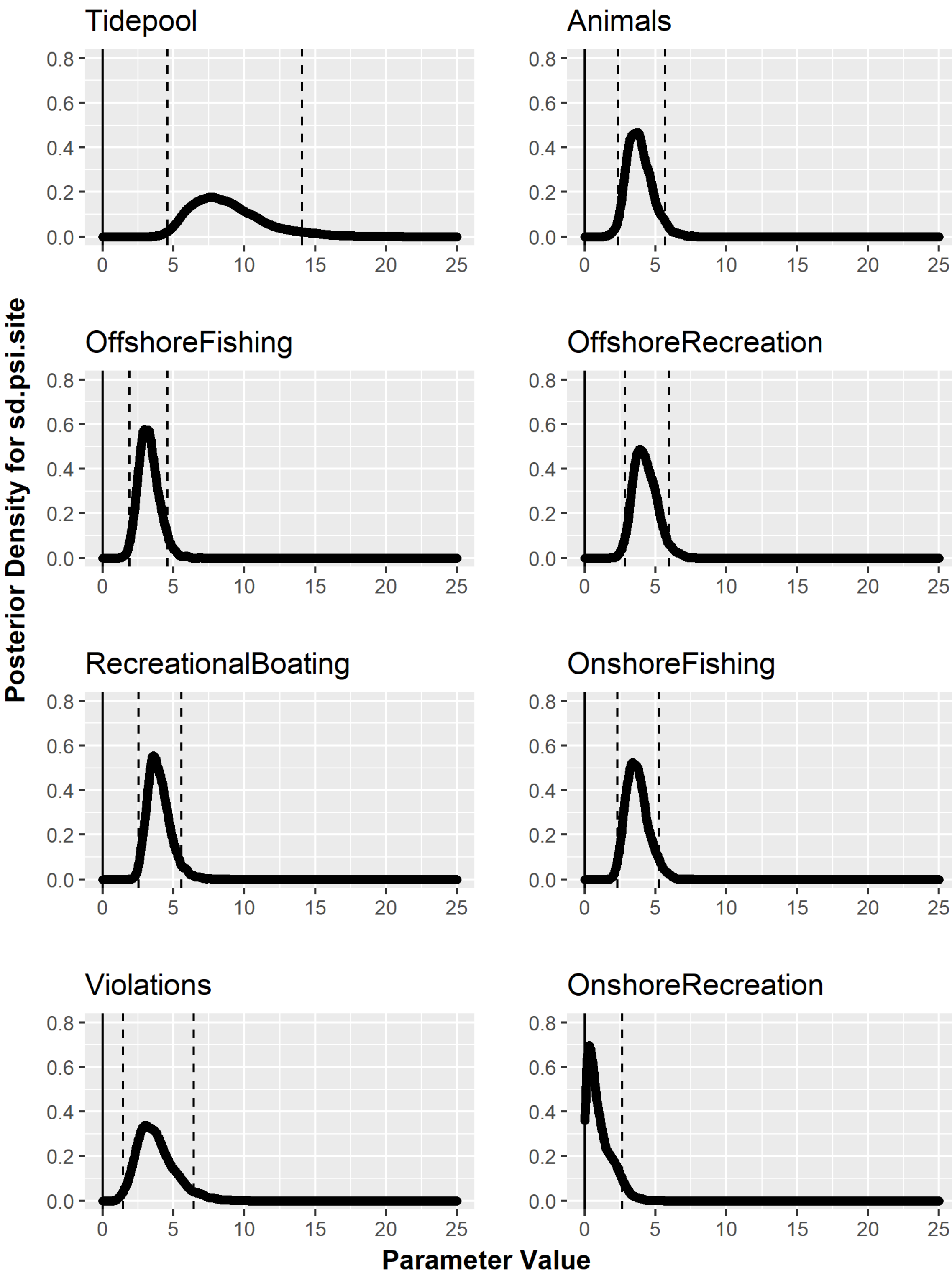


Figure 31: **Posteriors for four activities for the transect random effect on detection probability (which is allowed to differ for each year t), $\sigma_{\mathbf{tsect},t}$.** Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

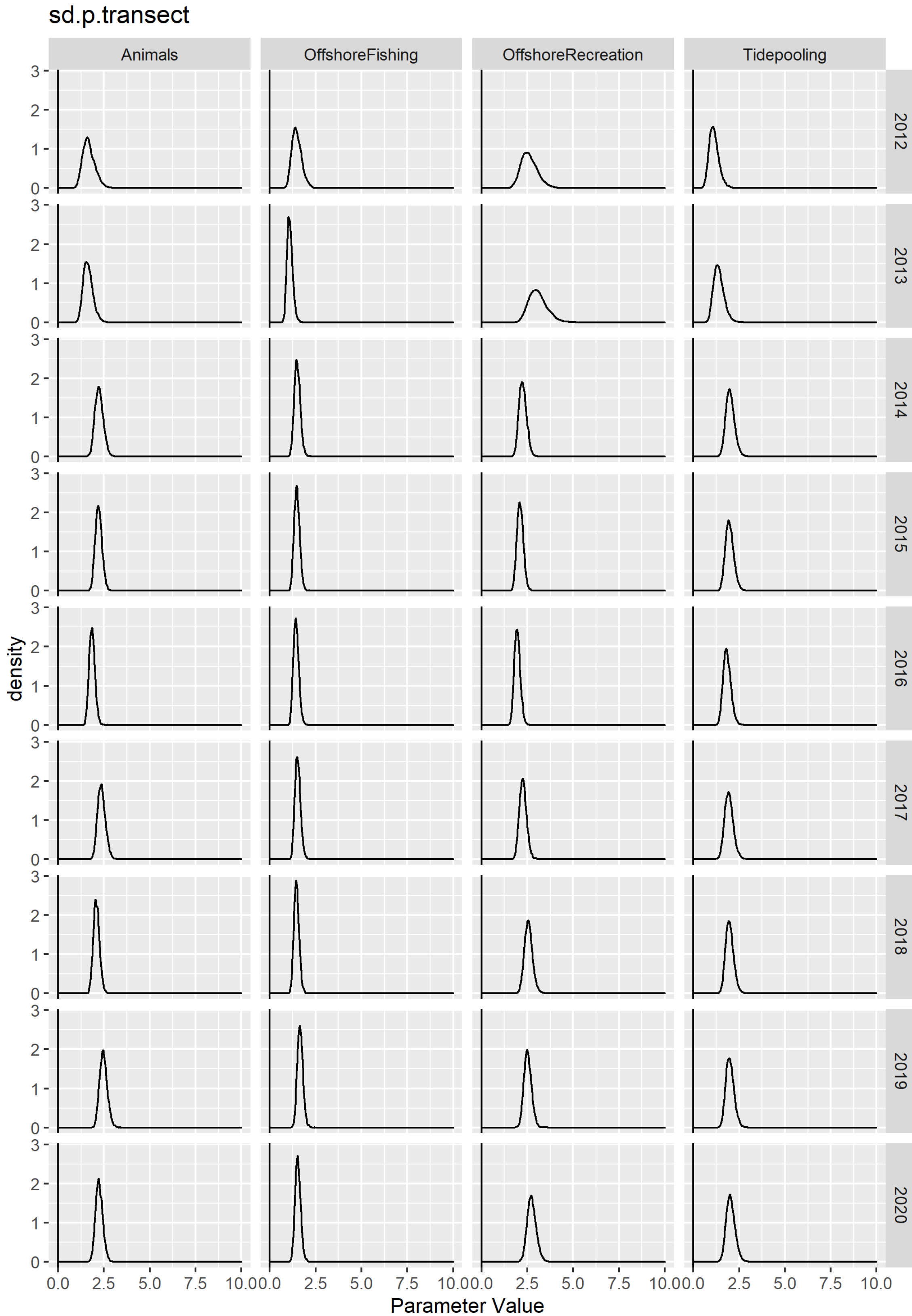


Figure 32: **Posteriors for four activities for the transect random effect on detection probability (which is allowed to differ for each year t), $\sigma_{\mathbf{tsect},t}$.** Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

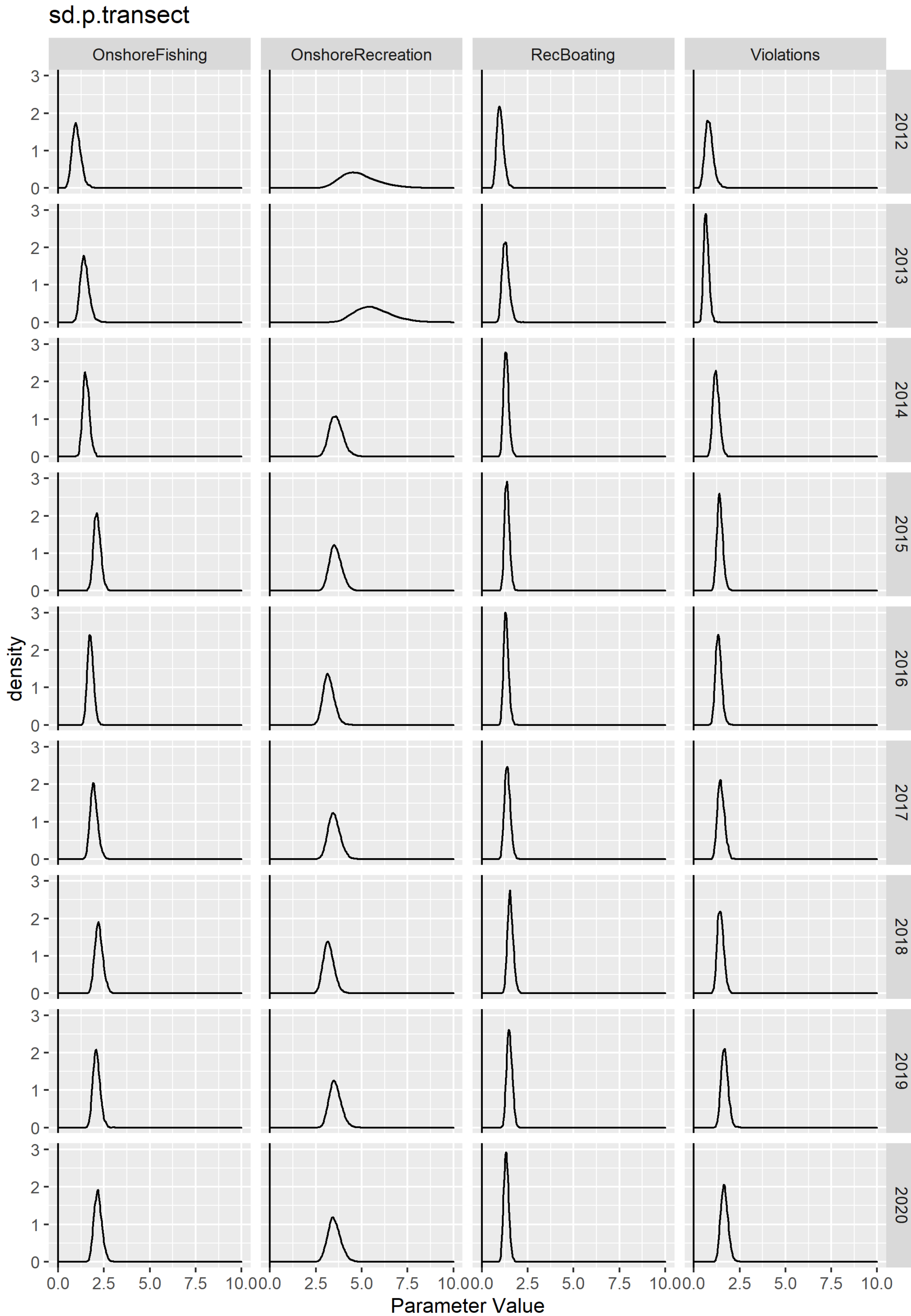


Figure 33: **Posteriors for all activities for baseline detection probability, $p_{\mathbf{base}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison. Onshore recreation has a high baseline probability of occupancy, consistent with the high number of "presences" in the dataset for that activity.

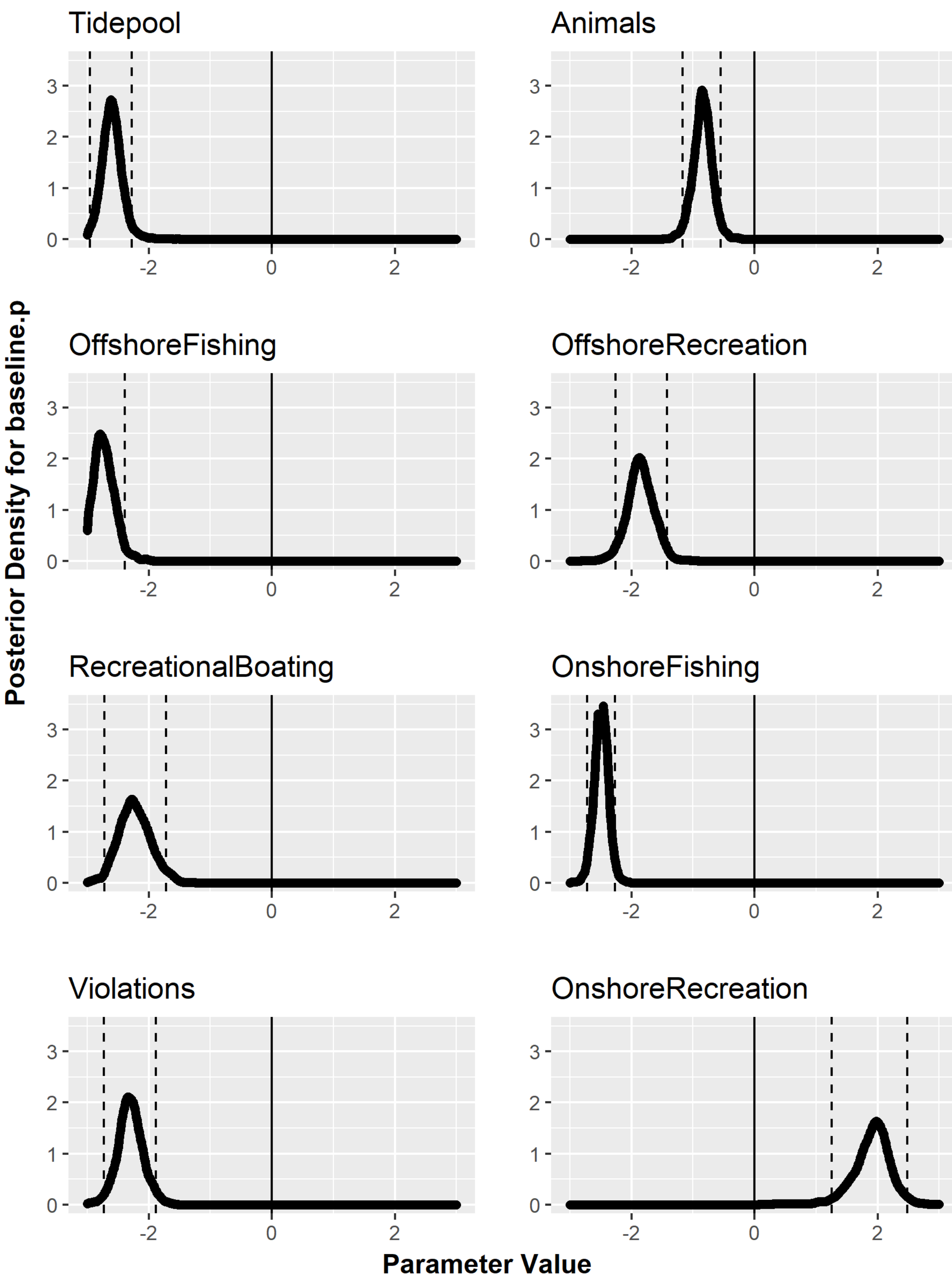


Figure 34: **Posteriors for all activities for the year random effect sd on detection probability, $\sigma_{\mathbf{yearDet}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

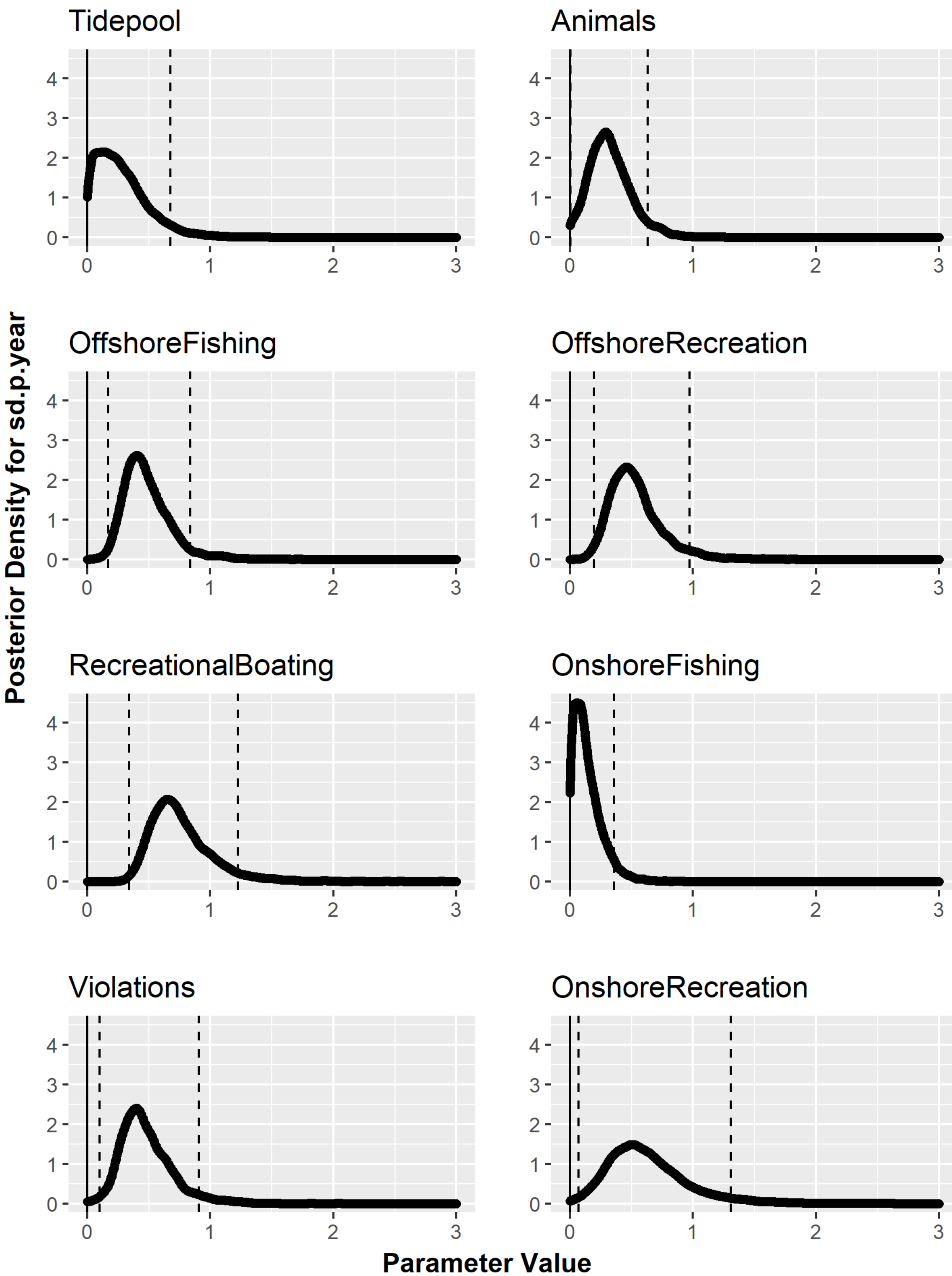


Figure 35: **Posteriors for all activities for the random effect standard deviation of the linear interaction with the day of year on detection probability, $\sigma_{\mathbf{lin}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

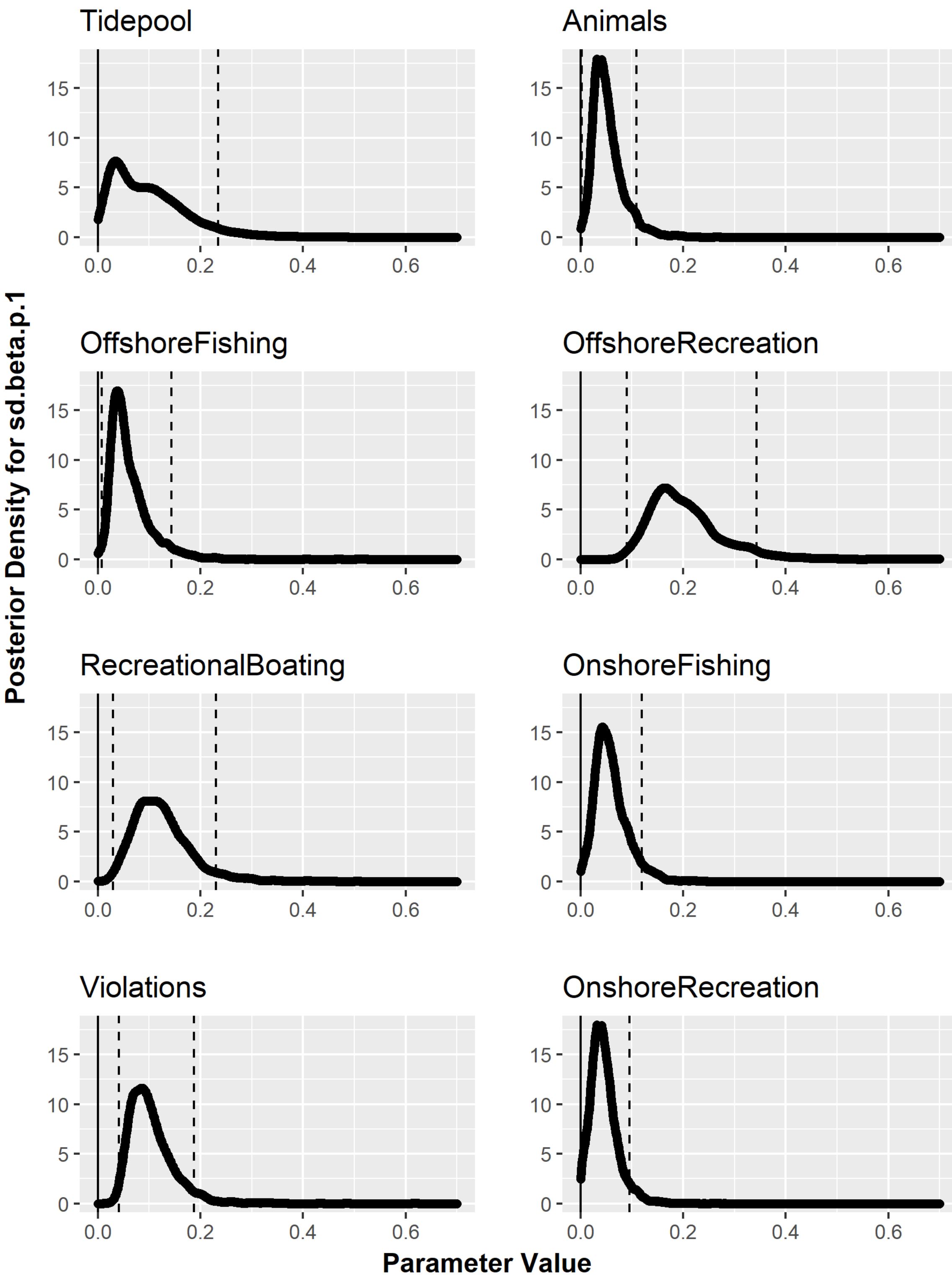


Figure 36: **Posteriors for all activities for the random effect mean for the linear interaction with the day of year on detection probability, $\mu_{\mathbf{lin}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

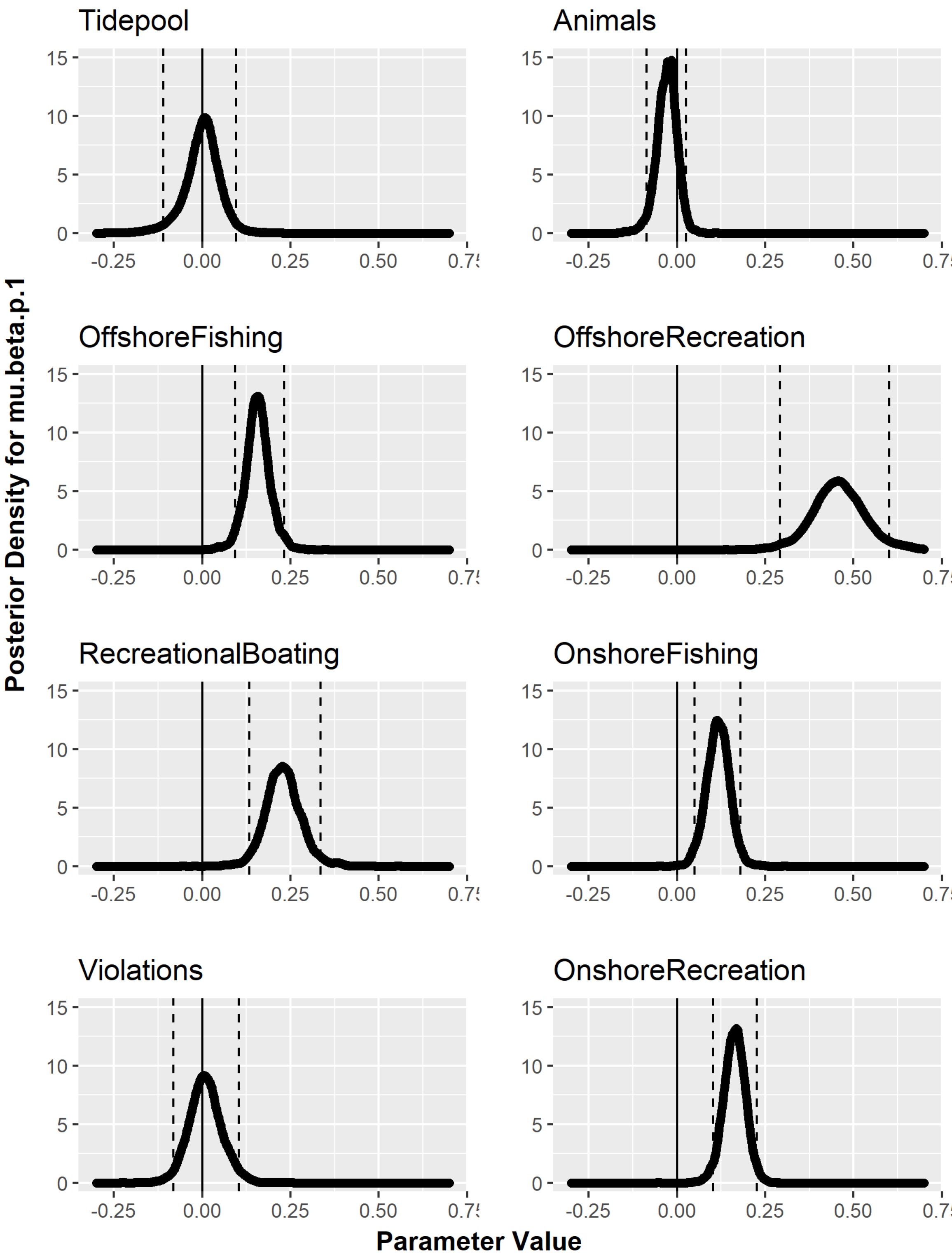


Figure 37: **Posteriors for all activities for the random effect standard deviation of the quadratic interaction with the day of year on detection probability, $\sigma_{\mathbf{quad}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.

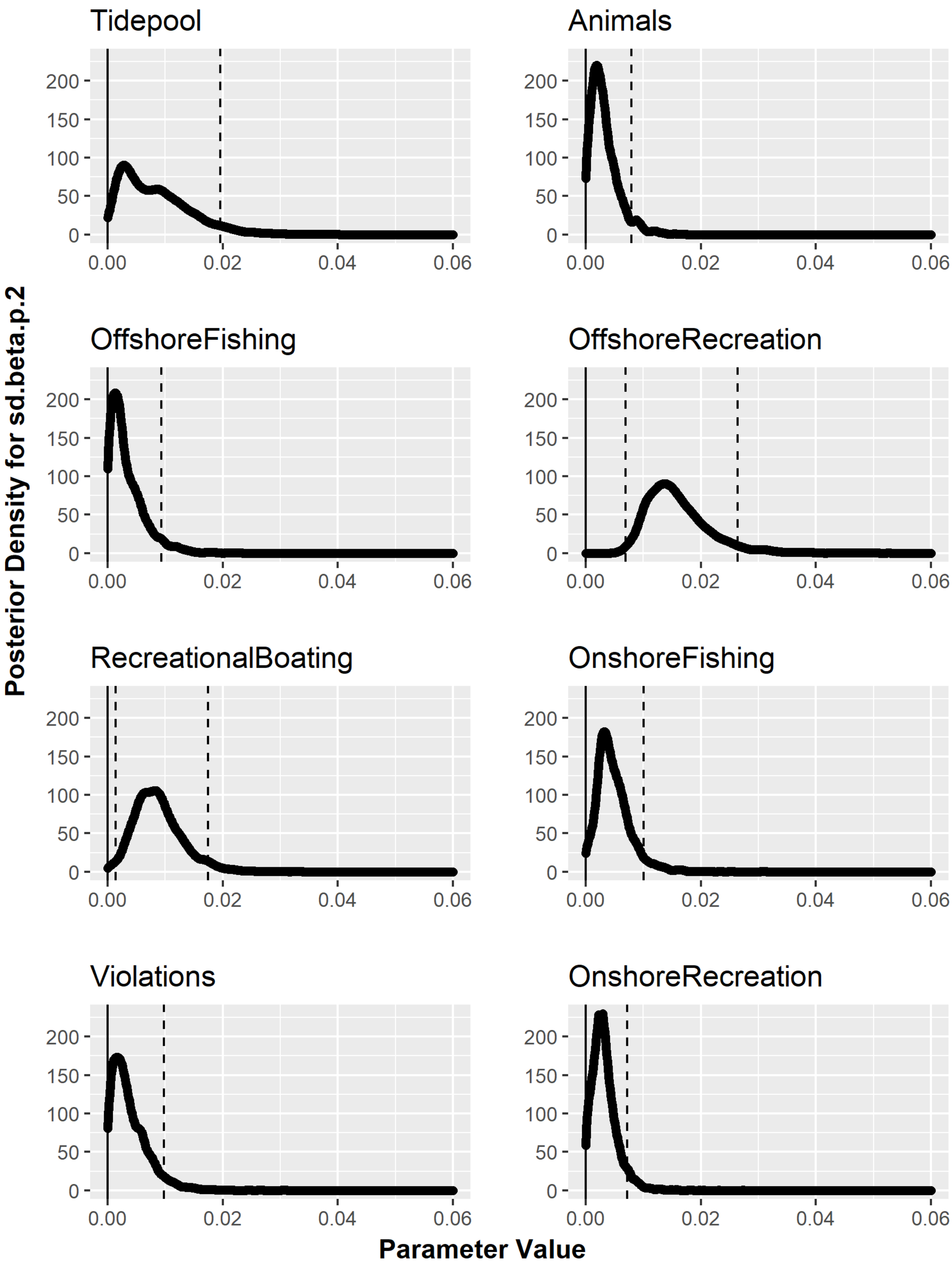


Figure 38: **Posteriors for all activities for the random effect mean for the linear interaction with the day of year on detection probability, $\mu_{\mathbf{quad}}$.** Vertical lines are 95% credible intervals, shown as a visual guide. Note that posteriors from different activities are shown together for qualitative rather than statistical comparison.