Cumberland Piedmont Network

National Park Service
Inventory and Monitoring Division

Monitoring Cave Aquatic Biota at Selected Parks in the Cumberland Piedmont Network

Supplemental Materials—Examination of the Feasibility of N-Mixture Abundance Models for Monitoring Cave Aquatic Biota via Direct Observation



ON THE COVER

Clockwise from top left: Unidentified cave amphipod, *Caecidotea* sp. (Kurt Lewis Helf), *Palaemonias ganteri* (Michael Durham), *Gyrinophilus palleucus* (Kurt Lewis Helf), *Orconectes pellucidus*, *Typhlichthys subterraneus* (Rick Olson).

Monitoring Cave and Aquatic Biota at Selected Parks in the Cumberland Piedmont Network

Supplemental Materials—Examination of the Feasibility of N-Mixture Abundance Models for Monitoring Cave Aquatic Biota via Direct Observation

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Revision Log

Version numbers will be incremented by a whole number (e.g., Version 1.3 to Version 2.0) when a change is made that significantly affect requirements or procedures. Version numbers will be incremented by decimals (e.g., Version 1.6 to Version 1.7) when there are minor modifications that do not affect requirements or procedures for publication in the series.

Revision Date	Author	Changes Made	Reason for Change	New Version #

Summary

The proposed Cumberland Piedmont Network (CUPN) Cave Aquatic Biota sampling effort cannot produce reliable estimates of abundance at the overall cave scale, let alone for two or more separate basins, for any but the most abundant and detectable species. A wide range of allocations of effort among varying transect lengths, transect numbers, and the number of within-year revisits had only limited effect. Given the range of abundances and detectabilities in the pilot data, only the most abundant species had low probabilities of either spurious estimates (five times or more than the true abundance) or failure of the hierarchical model to even generate an estimate for the single-year estimates of densities. The results for temporal trends are more ambiguous. Trend estimation pools data across multiple years, so there is more information to work with. However, power to detect 5 or 10% per year declines before abundances are halved was adequate only for higher abundances. Further, while the trend estimates were unbiased in that the averages across 500 or more simulations were centered on the true (simulated) values, the 95% confidence intervals included the true value as few as 30% of the time for high abundances and many short transects. This indicates false certainty about trend estimates, and thus substantial rates of false positives for both positive and negative trends. Detection probabilities had modest effect on the power to detect trends, but higher detection probabilities had lower coverage for confidence intervals.

The results are something of an interaction of part of parameter space (low detection probabilities & abundances) where hierarchical models have little power to estimate population sizes, and the more general lack of power to estimate status or trends for very rare species (Taylor and Gerrodette 1993).

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Background

Aquatic biota in cave streams occur at low densities and can be difficult to detect. The logistics of sampling in cave streams far from the entrances can be daunting, and limit the possible sampling effort. However, cave aquatic biota are important enough indicators of cave ecosystem status that they are a priority for monitoring.

Low abundance makes indices correlated to abundance very noisy, weakening the correlation between an index and absolute abundance, and increasing the need for detection-corrected estimates of absolute abundance. Hierarchical models can simultaneously estimate the detection probabilities and site occupancy or mean abundance from observations collected with imperfect detection. Such designs use removal sampling, double (or multiple) observers, or multiple within-season visits to provide information on the detection probabilities, then fit a hierarchical model for the abundance plus detection processes. The Cumberland Piedmont Network proposes to use multiple, within-season visits to transects in streams to estimate abundances of several cave aquatic species and repeat that sampling across years to estimate trends in those abundances.

The goals of this analysis are to determine the power or uncertainty of estimates of status and temporal trends in abundance, and to determine the optimal allocation of effort into number of transects, transect length, and number of revisits. This is a complement to and extension of Chris Sutherland's report (Sutherland 2016), and reflects a best-case scenario where individuals do not move in and out of transects between visits. His other points are addressed, too.

Design Parameters

Based on several email exchanges, a conference call, and a protocol development summary, the basic parameters for the proposed protocol are:

- Inferences are to be at the scale of basins. Not all basins can be sampled, but a two-stage design could select basins within Mammoth Cave National Park (MACA; perhaps stratified by N / S of Green River and basin size), then transects within the selected basins.

- The total effort is estimated at 4,800 meters (15,748 feet [ft]) of stream per year, the upper limit on the product of transect length, number of transects (across all basins), and number of revisits. Much of the travel time is from the surface to the cave stream; travel among transects within a stream segment represents negligible effort. Therefore, that overall threshold of 4,800 meters (15,478 ft) is a reasonable approximation of the sample sizes available for different designs. The Chris Sutherland summary appears to have been based on 8,000 meters (26,246 ft) effort (i.e., two hundred 20-m [65.5-ft] transects each visited twice [two teams]).

- Index of Biological Integrity (IBI) transect data exist for six species, with observations by stream and year. The provided data are ambiguous, as some cells have zeros and others have dashes. Dividing all counts by transect length and dropping both dashes and 0s, the median observed per 100 meters (328 ft) ranged from 5.6 for *Orconectes pellucidus* (ORPE) to 0.27 for *Stygobromus vitreus* (STVI). Using the Bridge Avenue estimated detection probabilities, these correspond to true abundances of 18.7 per 100 meters (328 ft) for ORPE and 0.66 per 100

meters (328 ft) for STVI. Using means instead of medians, and not dropping 0s, increases the estimated abundances per 100 meters (328 ft) to 39.5 for ORPE and 0.92 for STVI.

- Estimates of detection probabilities were provided for four species in one area, from an occupancy model (species presence along 20-meter [65.5-ft] transects). Detectabilities ranged from 0.92 for ORPE (cave crayfish) to 0.27 for STVI (amphipod). Note that detection for occupancy is not equivalent to detection for abundances. If more than one individual occupies a site, the occupancy detection probability is the probability of detecting occupancy: at least one of the individuals present. At very low densities they are nearly equal; as densities increase to levels with many sites with multiple individuals, the occupancy detection probabilities become substantially higher than the individual detection probabilities.

- The abundances Chris Sutherland estimated from pilot data at Bridge Avenue ranged from 19 individuals per 20-meter (65.5-ft) transect for ORPE to one per transect for STVI, plus two species with so few individuals observed that no abundance estimates were possible. Chris Sutherland estimated detectabilities for four species based on the pilot data and the *N*-mixture model. *Caecidotea stygia* (CAST) was the highest at 0.73, ORPE was 0.3, and STVI was 0.41. Note, however, that these estimated detection probabilities have standard errors of 0.09 to 0.20 for ORPE, STVI, and *Typhlichthys subterraneus* (TYSU), so they very well could be less than 0.2 or greater than 0.5.

The lack of solid pilot estimates for densities and detection probabilities is not as much of an issue as I initially thought. This protocol is not about monitoring for a single species, but rather for multiple species inhabiting the cave streams. Therefore, it is appropriate to perform simulations with a range of densities and detection probabilities, and cast the decision as not about the design with the most power for a particular individual species, but instead which design has acceptable power for the widest range (or lowest values of) densities and detection probabilities. Alternatively, the simulation results might be thought of as showing what ranges of species densities and detectabilities might reasonably be monitored via this approach.

Fundamental Tradeoffs

One major portion of this analysis is the fundamental sampling design optimization question: given a constraint on the total effort, what allocation of that effort gives the best information? Best can be defined as lowest expected (average) uncertainty (narrowest confidence intervals), or lowest chance of giving widely erroneous estimates. Ignoring travel costs and time to get in and out of the water, the total effort per year of searching 4,800 meters (15,748 ft) of cave streams can be allocated among transect length per site, number of revisits, and number of sites.

Transect Length

For a given density, increasing the transect length increases the expected abundance (lambda) in each transect. Two secondary effects not included in these analyses are reduction in temporary unavailability (movement of an individual across the endline of a transect between revisits), and averaging out small spatial scale clumpiness to more Poisson-like variation. The former is irrelevant for (nearly) simultaneous double observers, and for repeated visits it is driven by the unknown characteristic movement distance of individuals relative to length of the transects. There is no pilot data on spatial scales and degrees of aggregation or clumpiness for the species of interest. However, given the low mean abundances per 10 meters (32.8 ft), any aggregation must average much less than one clump per 10 meters (32.8 ft), so only the very longest transects might appreciably average out clumpiness.

Number of Revisits

The number of revisits drives the estimates of detection probability. For species with moderate to low detection probabilities, larger numbers of revisits increases the number of individuals present that are detected at least once. There is no hard and fast rule for the optimal number of revisits for a given detection probability.

Number of Transects

The number of transects or sites is the effective sample size for the model estimations. Larger sample sizes more closely represent the target population, and have greater statistical power, or, equivalently, have narrower confidence intervals about their estimates.

All three of these components have diminishing returns: more is better, but the benefits are concave functions. Therefore, the optimization problem is a three-way marginal value problem with interactions. The simulations are a more tractable way to address this optimization than any analytical approach.

Estimation of Single-Year Abundance

The ability to estimate single-year abundance or status was tested by simulating large numbers of data sets from the sampling process (Fiske and Chandler 2011; Kéry and Royle 2017; R Core Team 2017). The three design parameters of total effort (4,800 meters [15,748 ft] for inference to the entire cave system, 2,400 meters [7,874 ft] for inference to two basins, 1,200 meters [3,937 ft] for inference to four basins), transect lengths (10–50 meters [32.8–164 ft]), and number of revisits (2–6) were varied, with the number of transects computed from the effort divided by the transect length and number of revisits.

Table A-1. Design parameters for simulated datasets used to test estimates of single-year CAB abundance.

Parameter	Unit	Values
Total Effort	In m	4800, 2400, 1200
Abundance	Per m	.01, .05, .1, .2, 1
Transect Length	In m	10, 20, 25, 30, 40, 50
Number of Revisits	--	2, 3, 4, 5, 6
Number of Transects	Effort/length/revisits	8, 10, 12, 14, 15, 16, 20, 24, 27, 30, 32, 40, 48, 60, 80, 120
Detection Probability	--	Uniform [0.01-0.99]

From these 450 parameter combinations, data were simulated with the appropriate number of sites (transects), Poisson counts of individuals in each transect (with lambda as the product of transect length times abundance per m). Then from that transect count, for each revisit a second binomial detection process determined how many individuals were observed in that transect at that revisit. For each of the 450 combinations of the first four parameter, 1,000 simulations were run with detection probabilities drawn from a uniform distribution. Such data simulate the best possible case, with no variation among sites or observers in detection probabilities, and no movement in or out of transects between revisits.

```
# Simulated Data

Data <- simNmix(nsite=bigT$nSite[Tsim],

                nvisit=bigT$nVisit[Tsim],

                mean.lam = bigT$abund[Tsim] * bigT$tLength[Tsim],

                mean.p=p[ii,Tsim],

                show.plot = F)       # Generate data set

umf <- try(unmarkedFramePCount(y = Data$C)) # Bundle data for unmarked
```

The N-mixture hierarchical model fit was the simplest possible, fitting intercepts or estimates for both the abundance and the detection probability.

```
# Hierarchical Model

Fm <- pcount(~1 ~1, umf, mixture='P', engine='C')
```

This model is a good fit for multiple observers at the same time, or for multiple visits to the same site for sessile or at least non-motile species where individuals will not move in and out of the transect across the endlines ("temporary immigration"). To the extent that individuals move at the scale of a few meters, this approximation is better for fewer longer transects and problematic when individuals move distances more than a few percent of the transect length.

Results

The results of the analyses of the simulated data are presented in three slightly different scalings in Figures A1-1 through A3-15. Figures A1-1 to A1-15 presents the raw (estimated) abundance per transect on the Y axis, where different transect lengths and abundances per m produce varying expected or true abundances per transect. Figures A2-1 to A2-15 presents the ratio of the estimated abundance to the true (simulated) value. Therefore 1.0 reflects an estimate exactly matching the true abundance, 0.5 is an estimate that is half of the true value, and 2.0 is an estimate double the true value. Figures A3-1 to A3-15 have the same ratio scaling of the Y axis as Figures A2-1 to A2-15, but Y values greater than 5 are truncated to 5, so that variation around 1 is still resolved despite some very large estimates. The truncated versions in Figures A3-1 through A3-15 present the essential information most clearly; the Figure A1-1 to A1-15 and Figure A2-1 to A2-15 versions are included for understanding what is happening in Figures A3-1 to A3-15. The figures are tiles of multiple graphs with differing transect lengths as columns and revisit numbers as rows, and the detection probability is the X axis within each graph. Each page is a separate combination of effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]) and abundance (0.1, 0.5, 1, 2, and 10 per 10 meters [32.8 ft]).

In all combinations of mean abundance and total effort, very low detection probabilities lead to a non-trivial fraction of simulations producing spurious estimates well more than twice the true value. The effect of transect lengths are most clear in Figures A2-1 through A2-15 (pages 16–30): within a row, more shorter transects reduces the threshold detection probability needed for eliminating spurious estimates, but greatly increases the magnitude of those spurious overestimates when they occur. Comparison among graphs on a page show that the allocation tradeoffs between transect lengths, number of revisits, and number of transects have modest effects. For simulations with more abundant species and park-wide inference (4,800 meters [15,748 ft] effort), large numbers of shorter transects performed somewhat better than fewer, longer transects, in terms of lower rates of failure to estimate and of spurious overestimates.

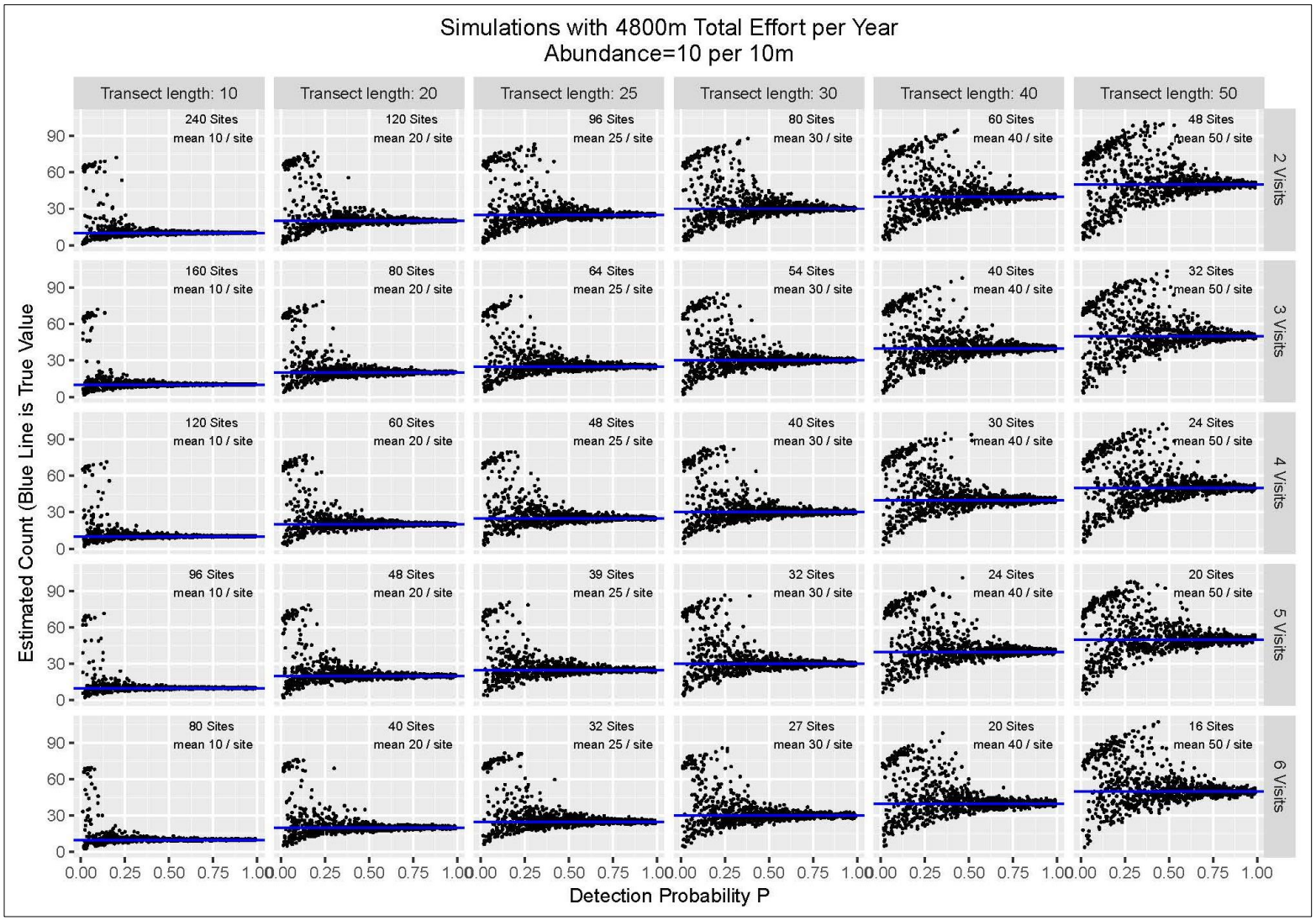


Figure A1-1. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 10 per 10 meters.

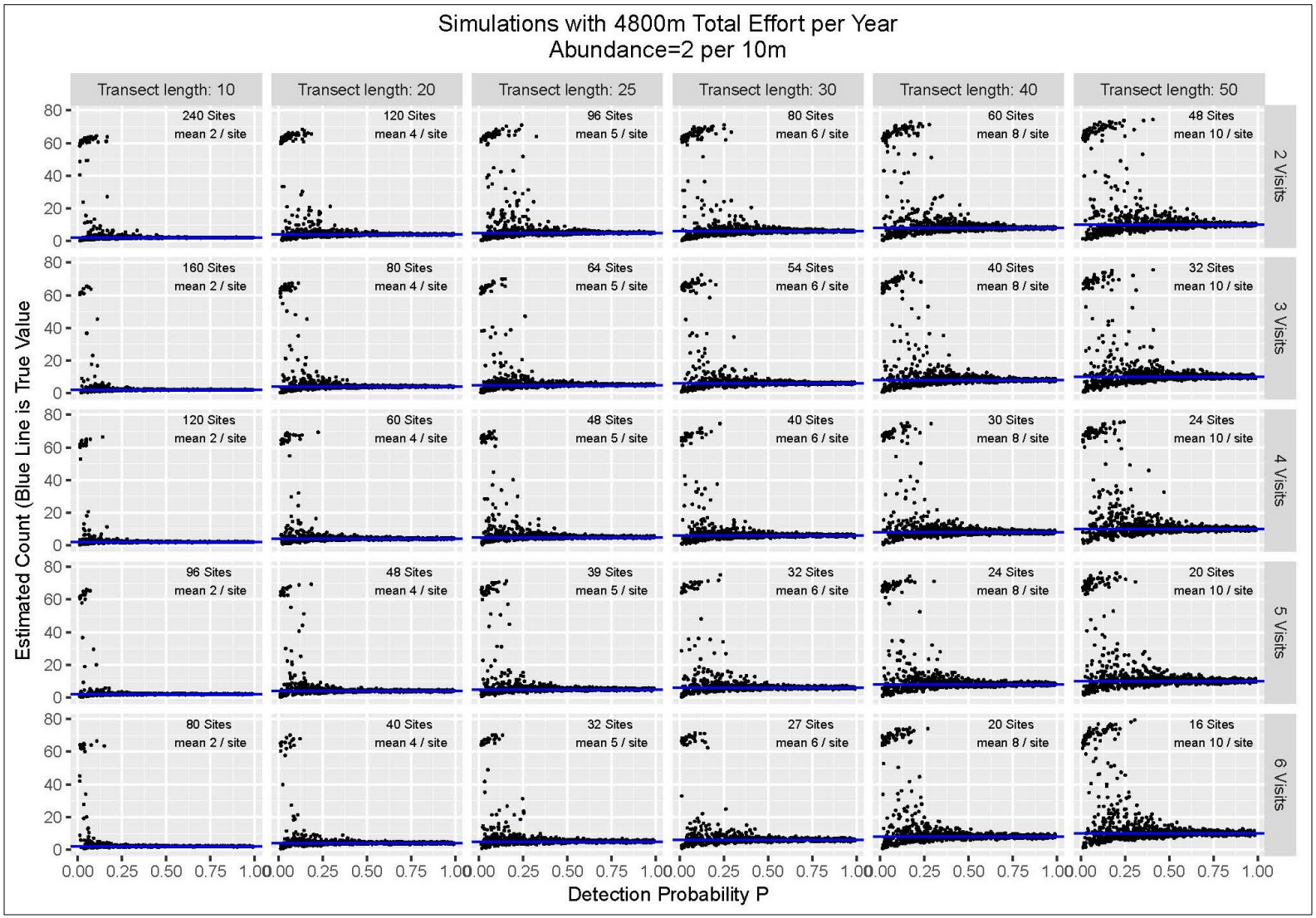


Figure A1-2. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 2 per 10 meters.

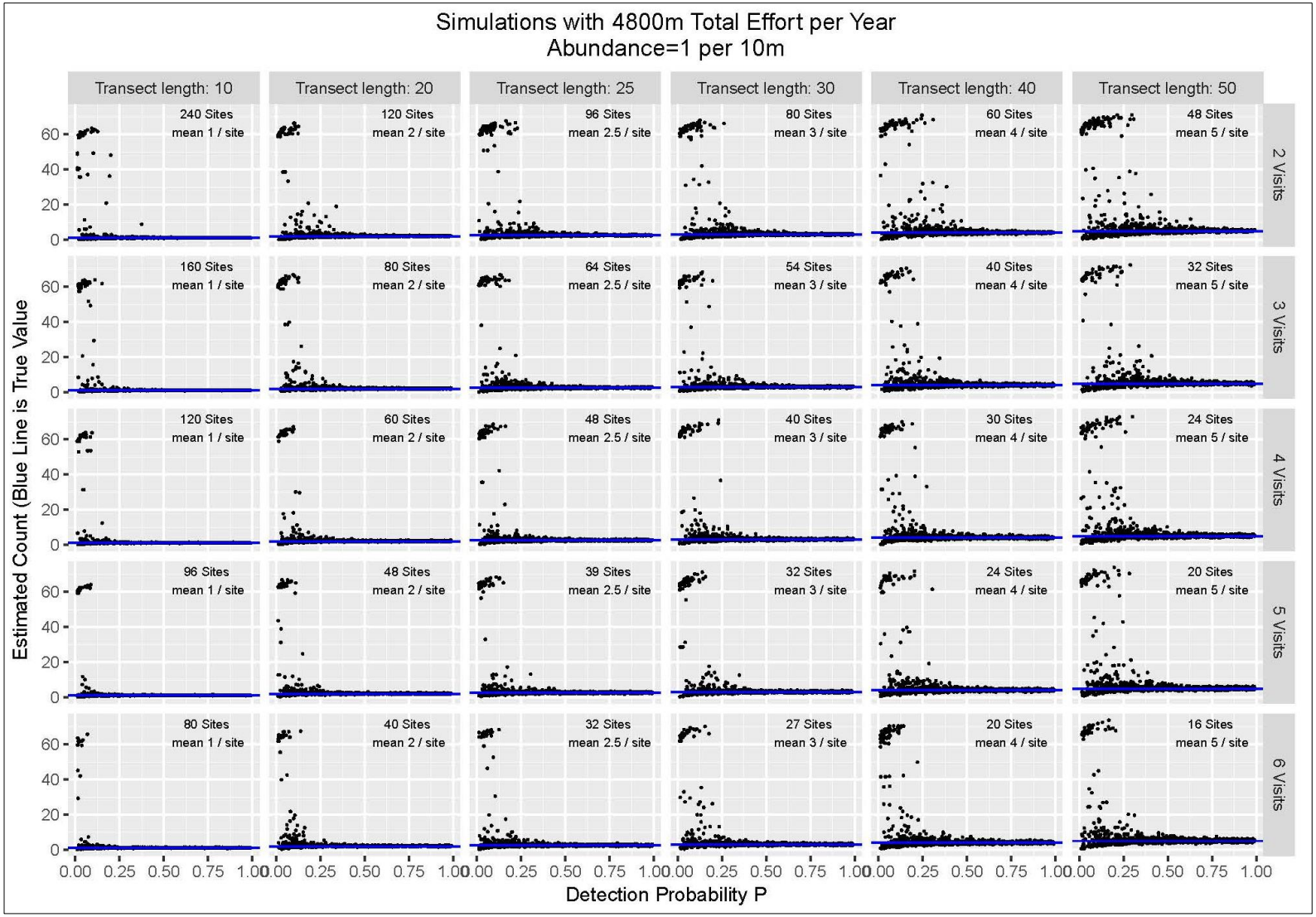


Figure A1-3. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 1 per 10 meters.

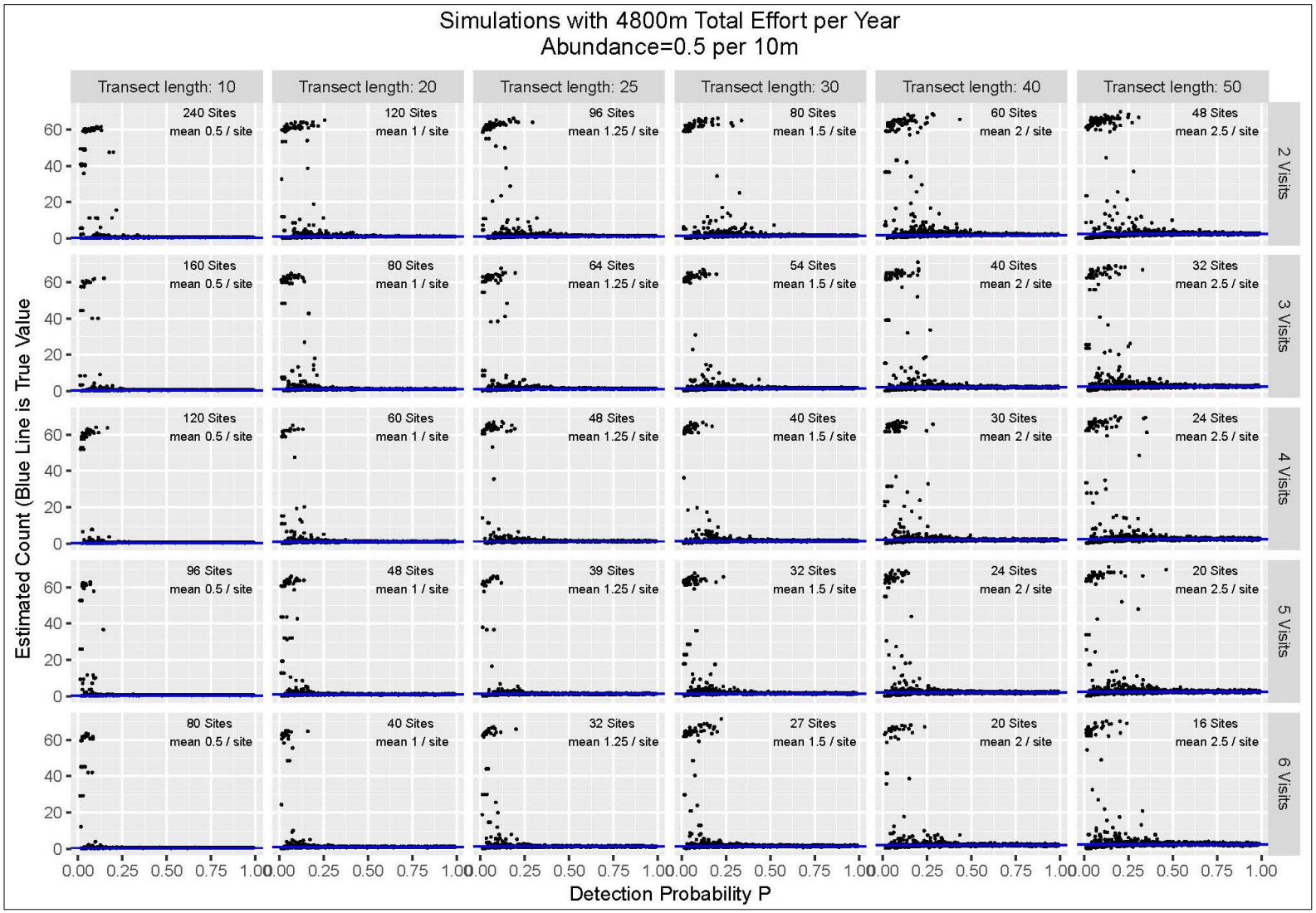


Figure A1-4. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 0.5 per 10 meters.

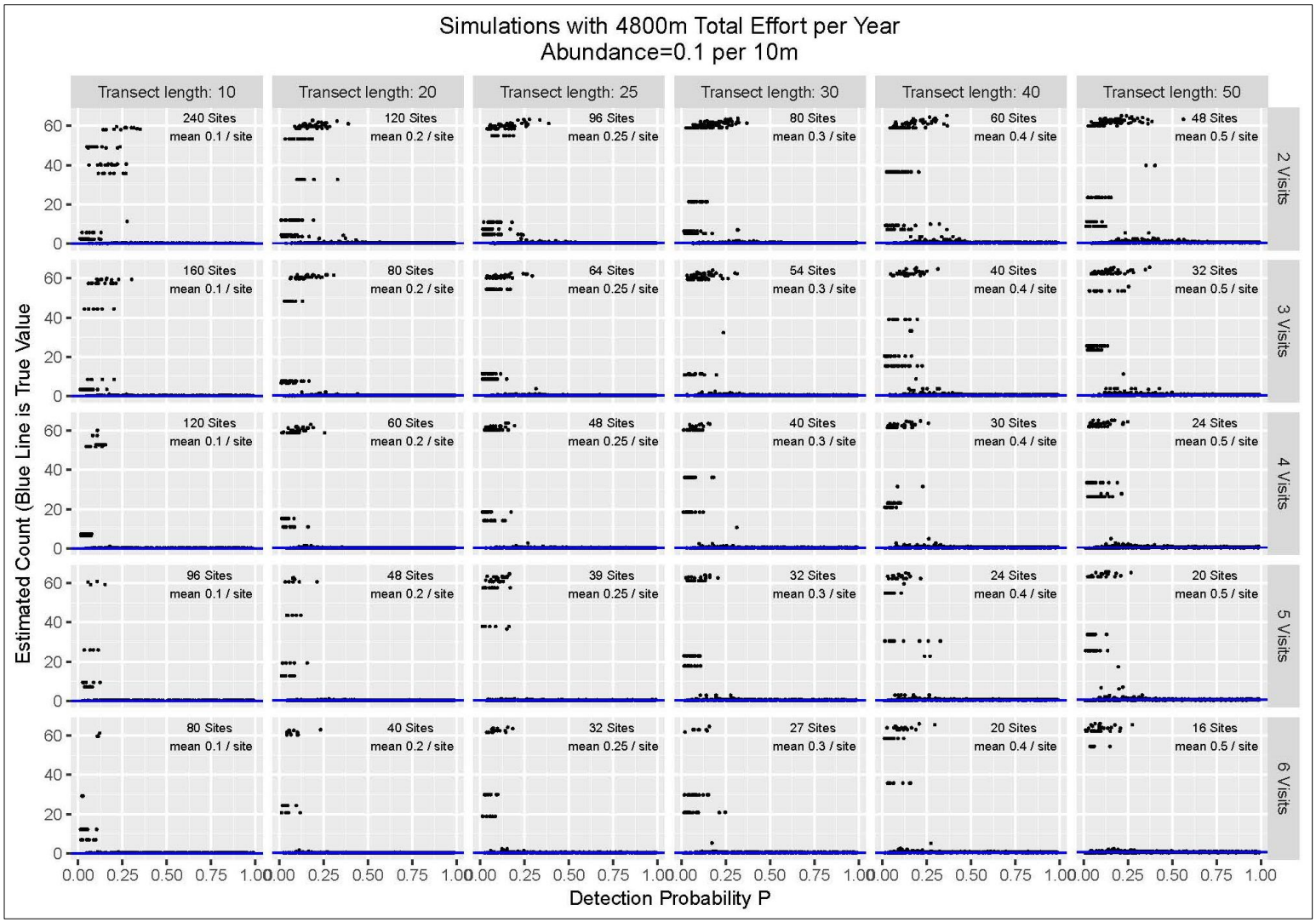


Figure A1-5. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 4,800 m Total Effort per Year. Abundance equals 0.1 per 10 meters.

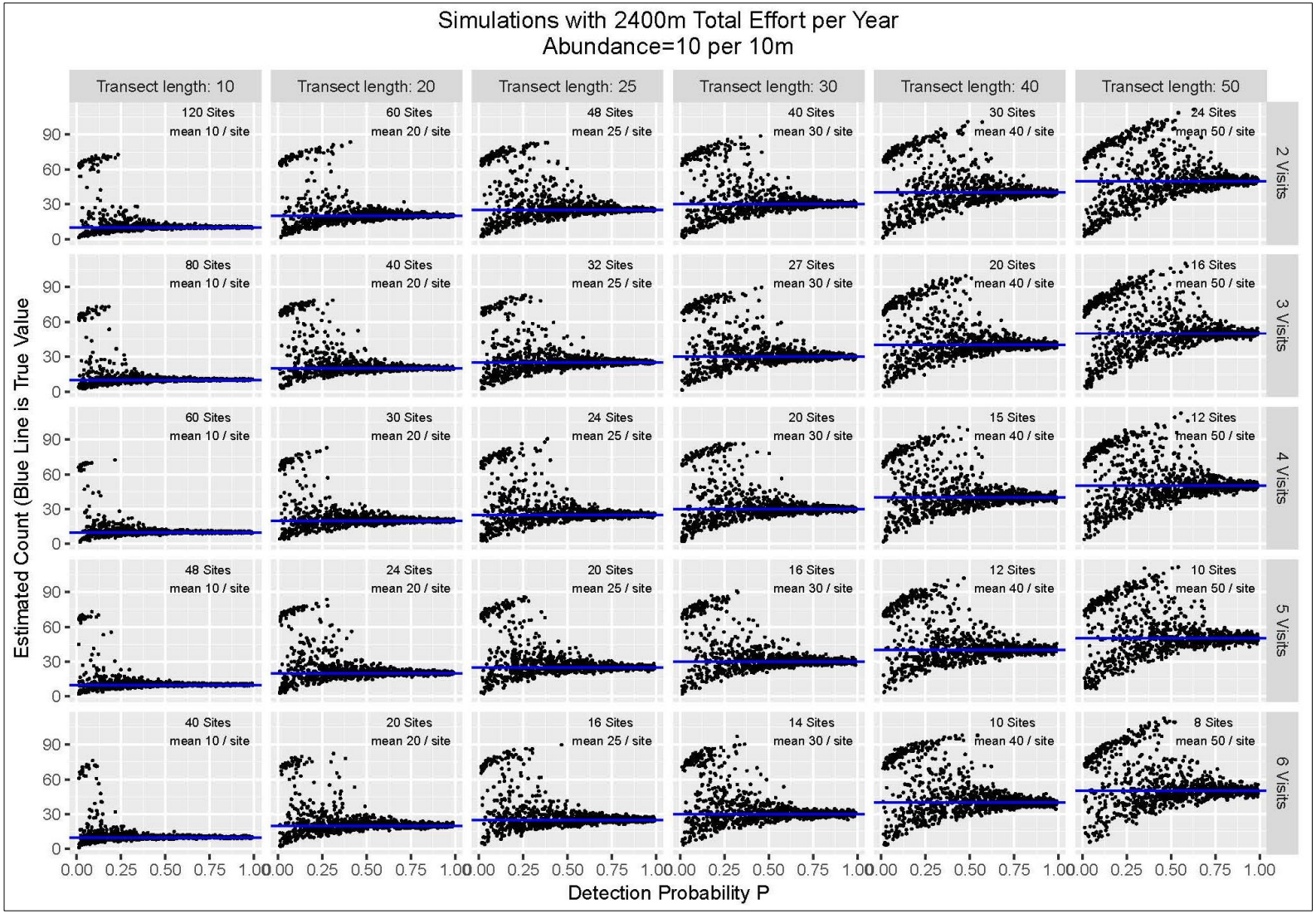


Figure A1-6. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 10 per 10 meters.

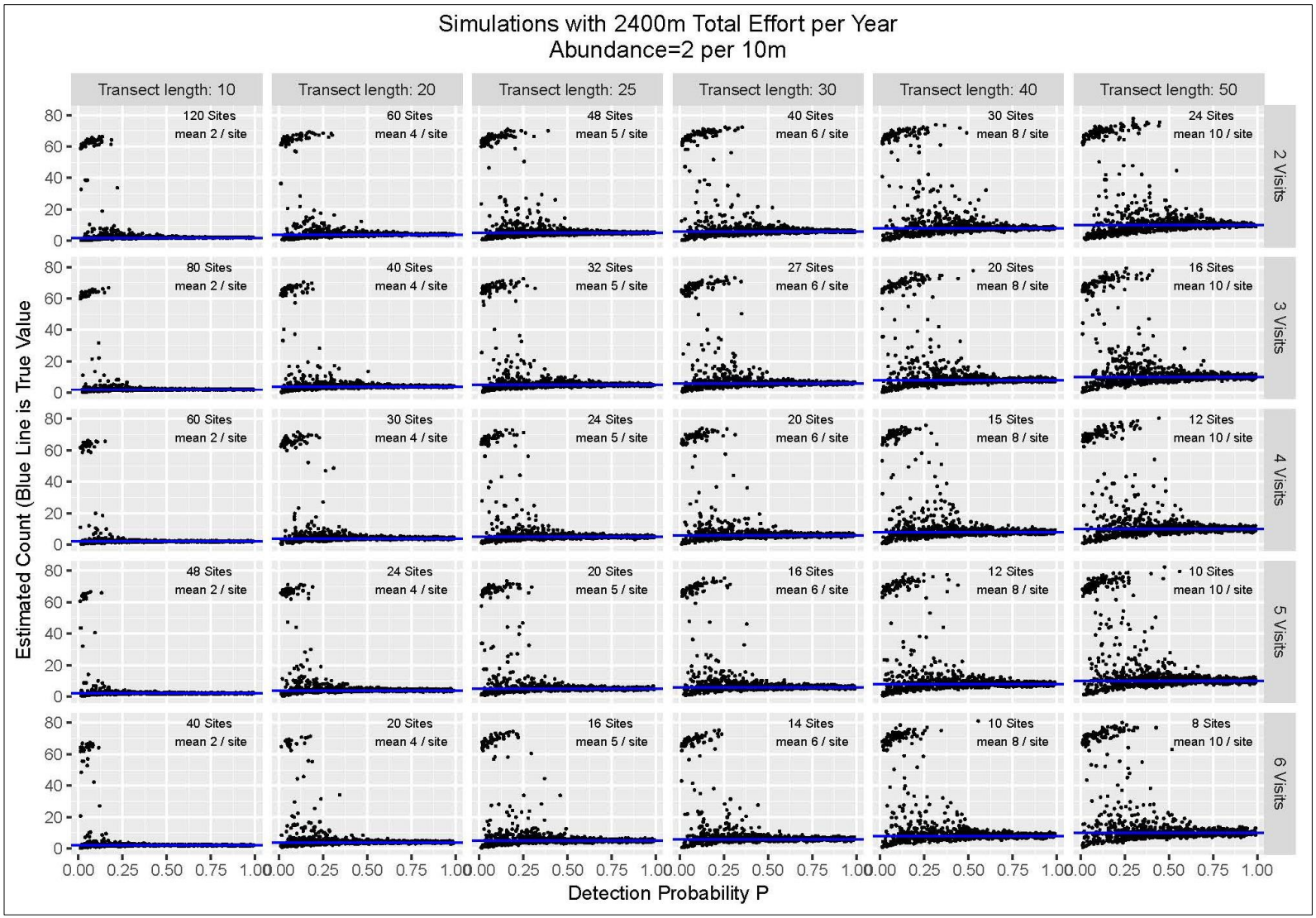


Figure A1-7. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 2 per 10 meters.

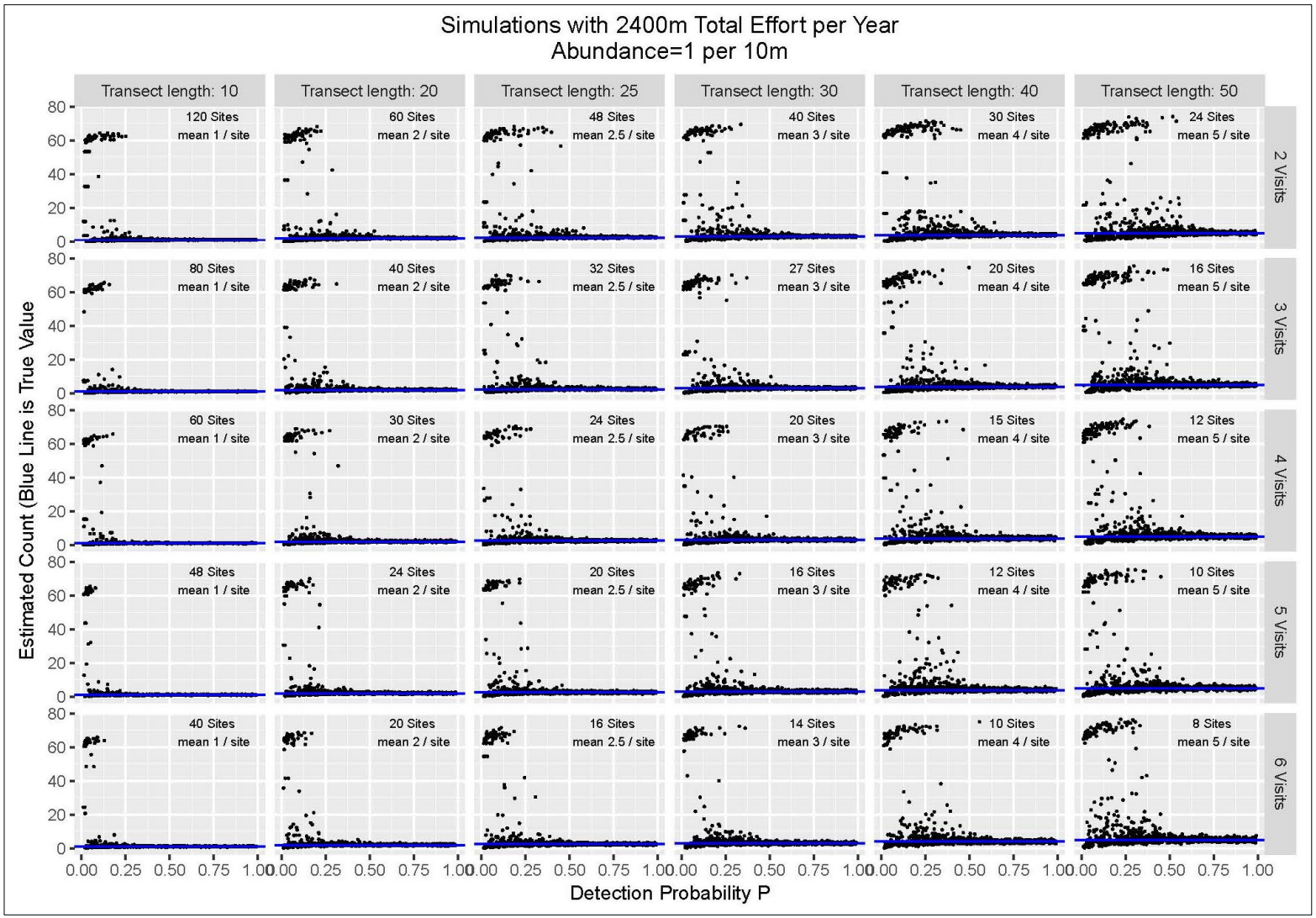


Figure A1-8. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per m times the transect length in meters. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 1 per 10 meters.

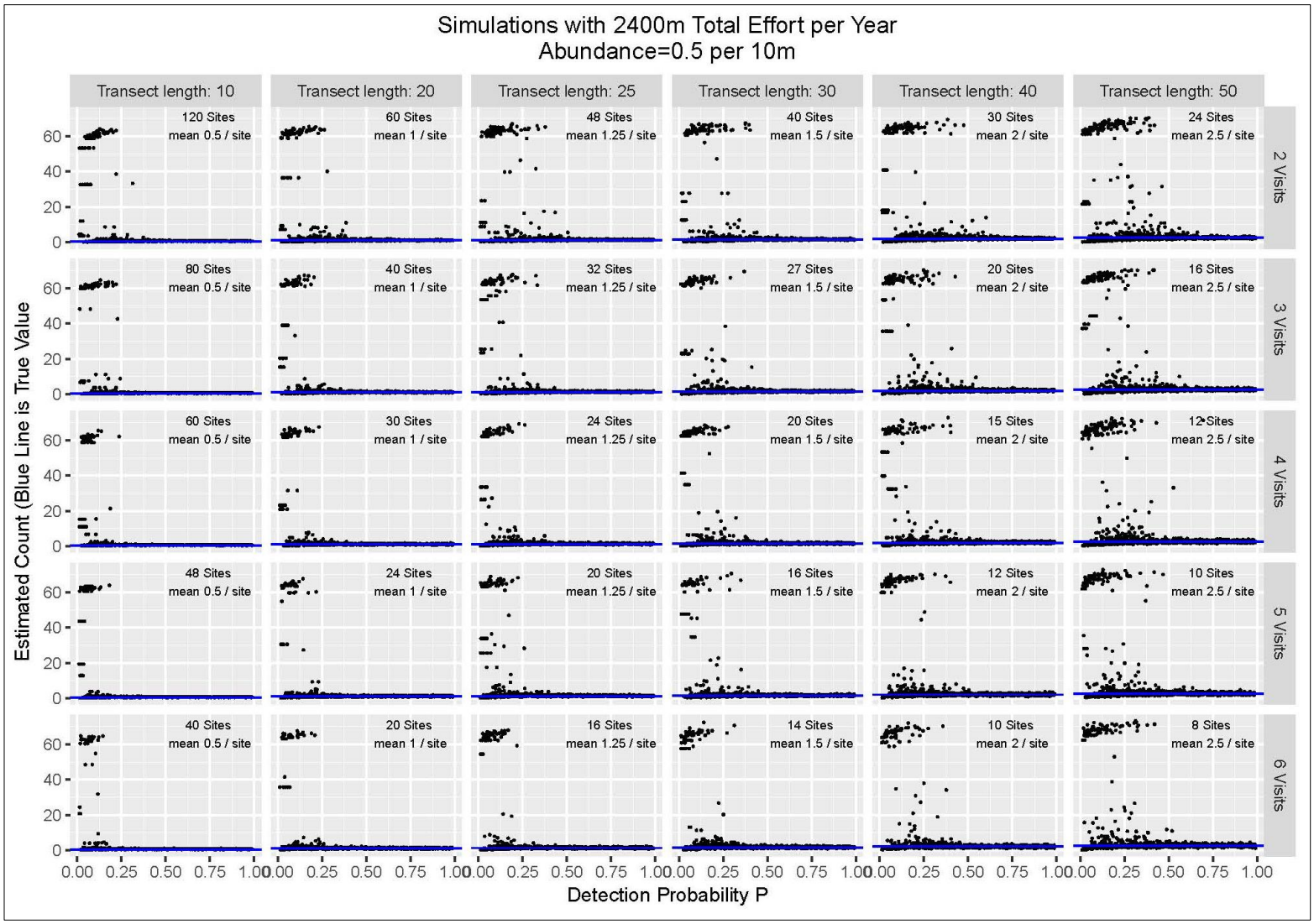


Figure A1-9. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 0.5 per 10 meters.

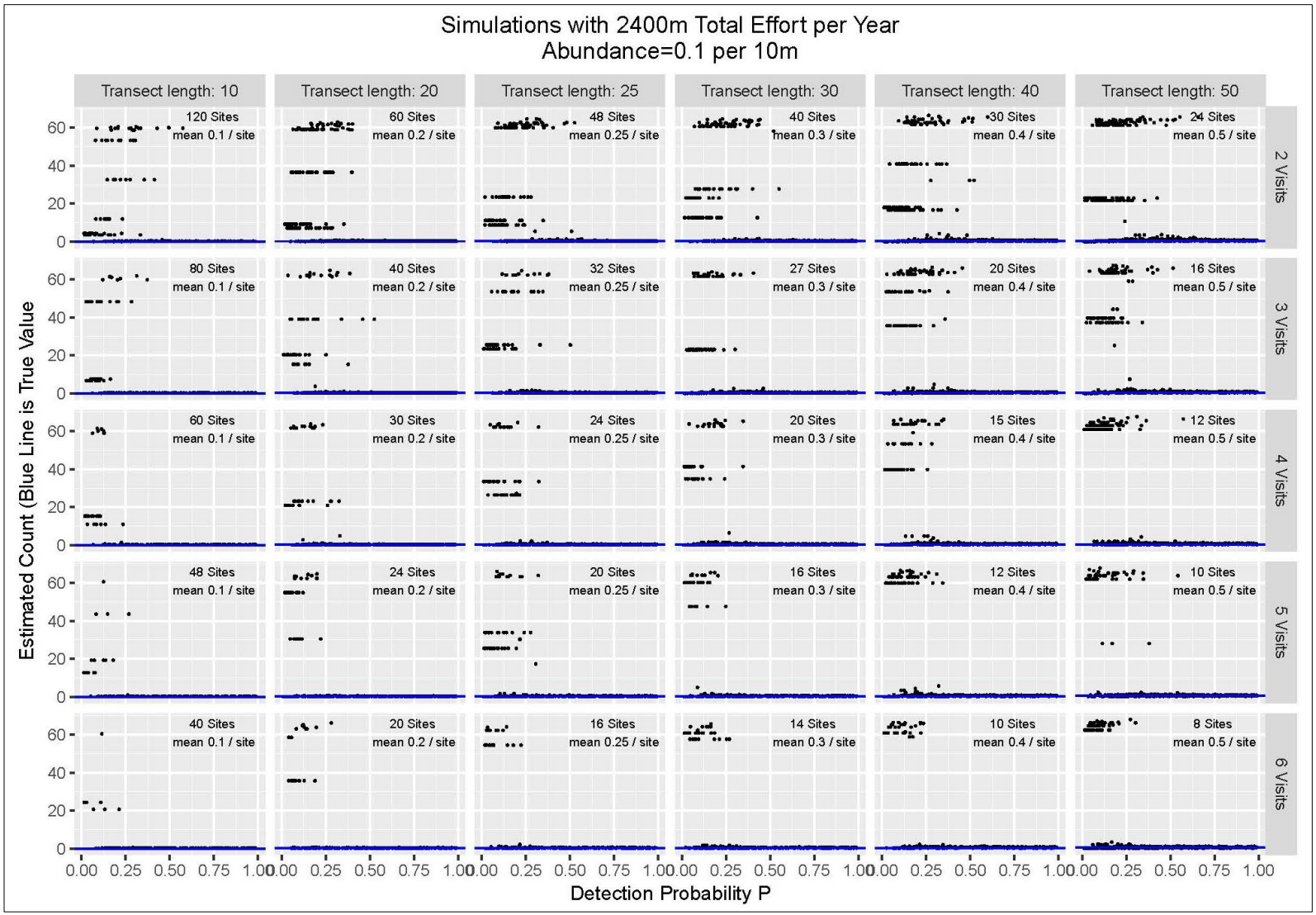


Figure A1-10. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 0.1 per 10 meters.

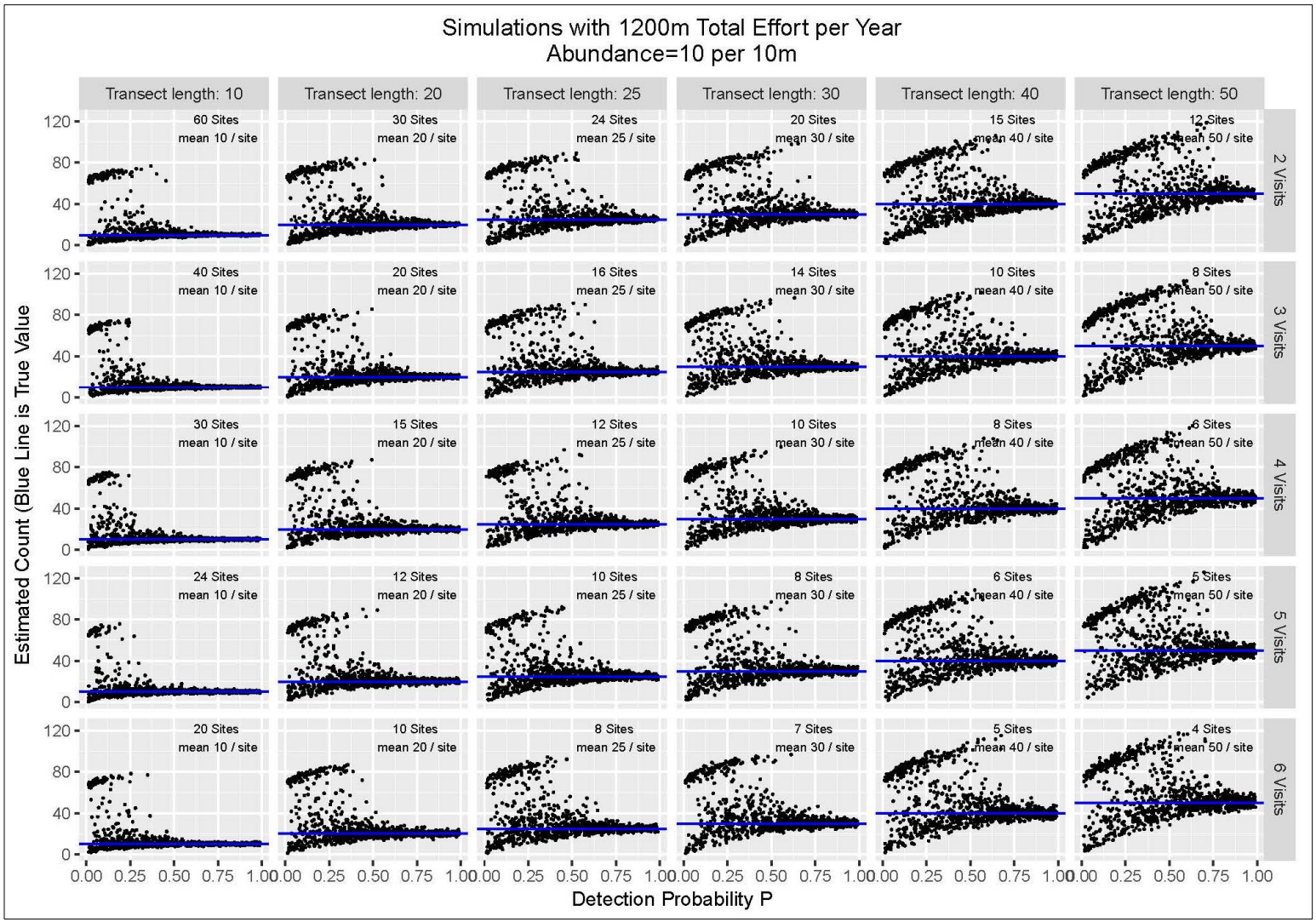


Figure A1-11. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 10 per 10 meters.

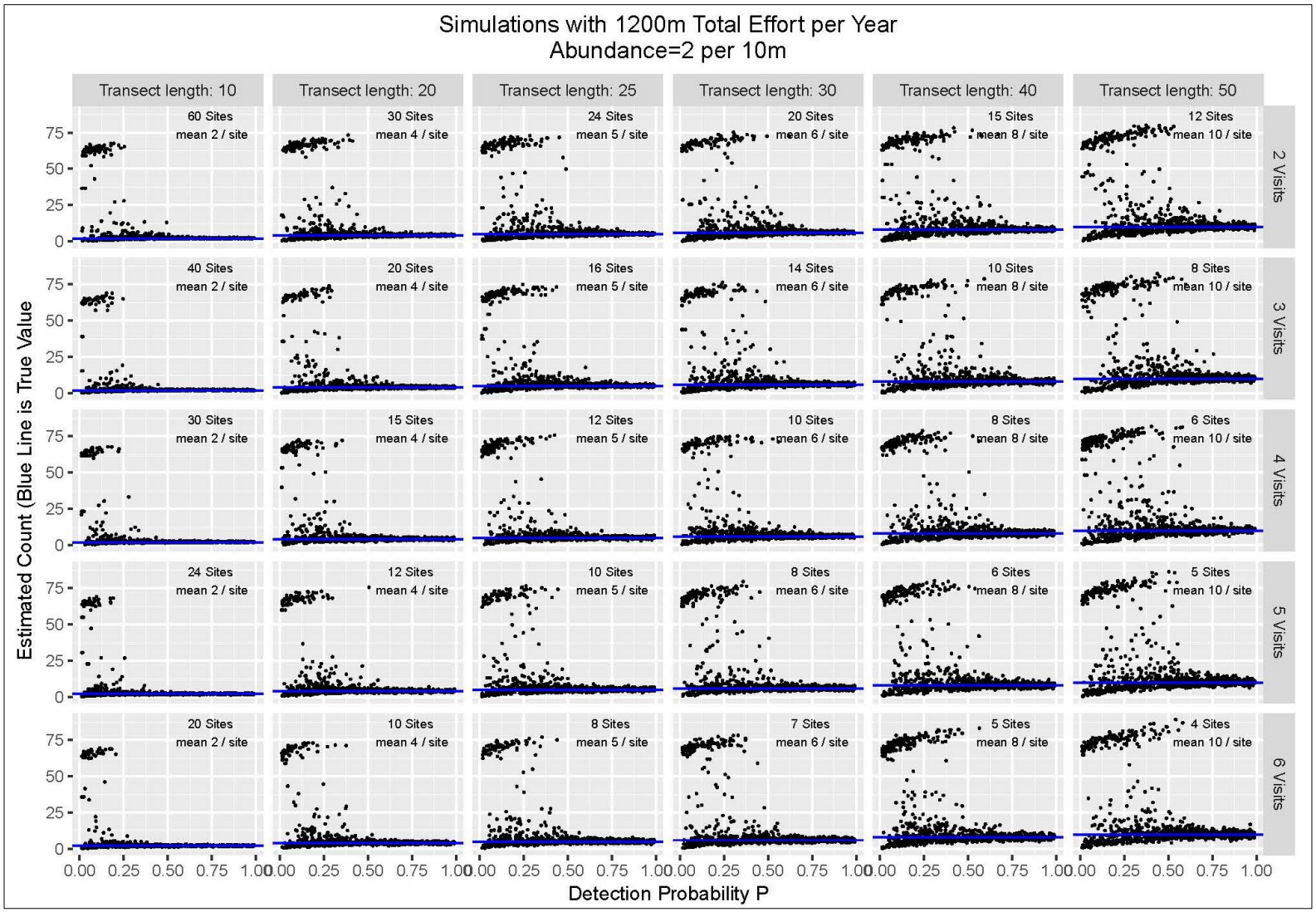


Figure A1-12. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals two per 10 meters.

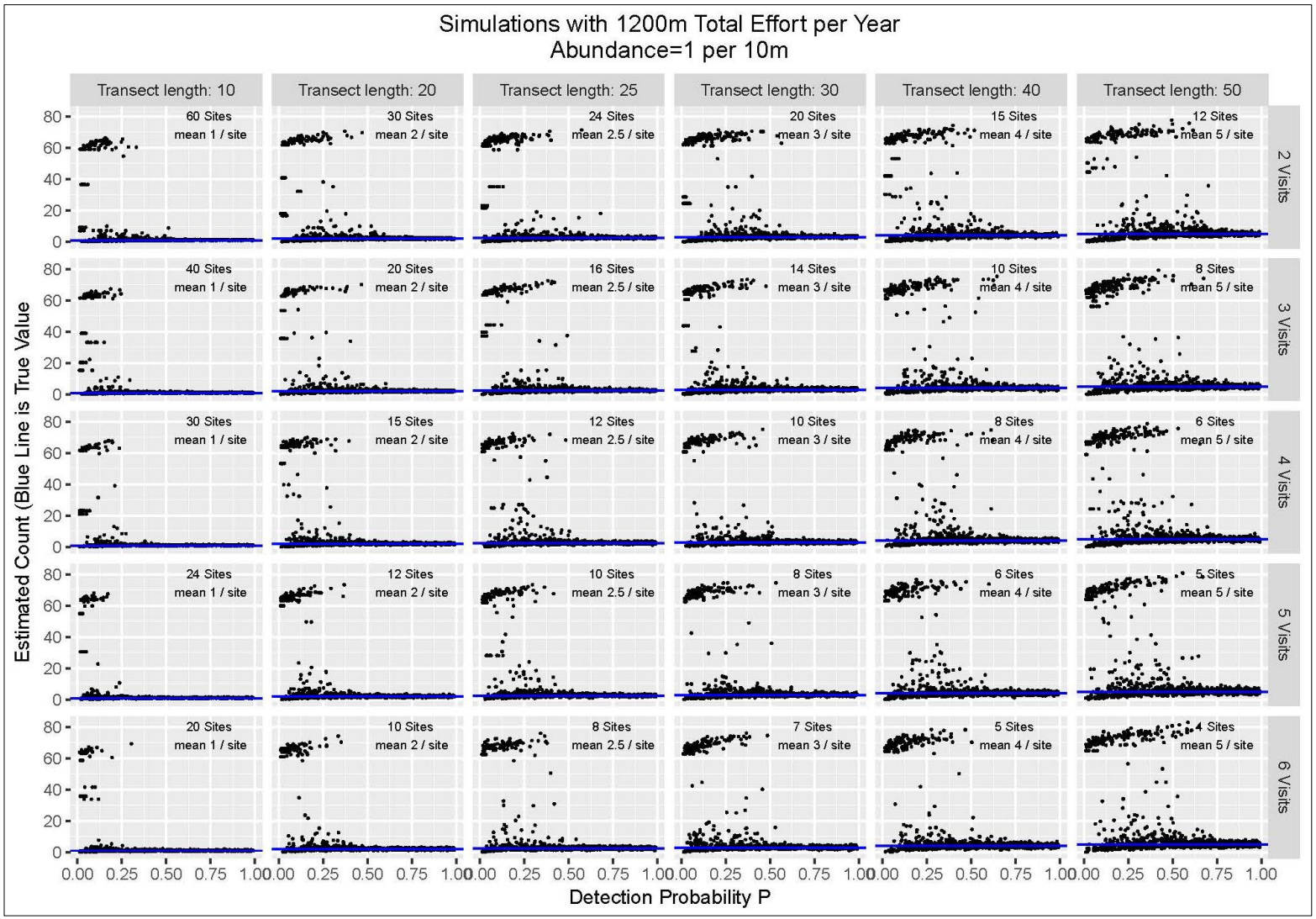


Figure A1-13. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals one per 10 meters.

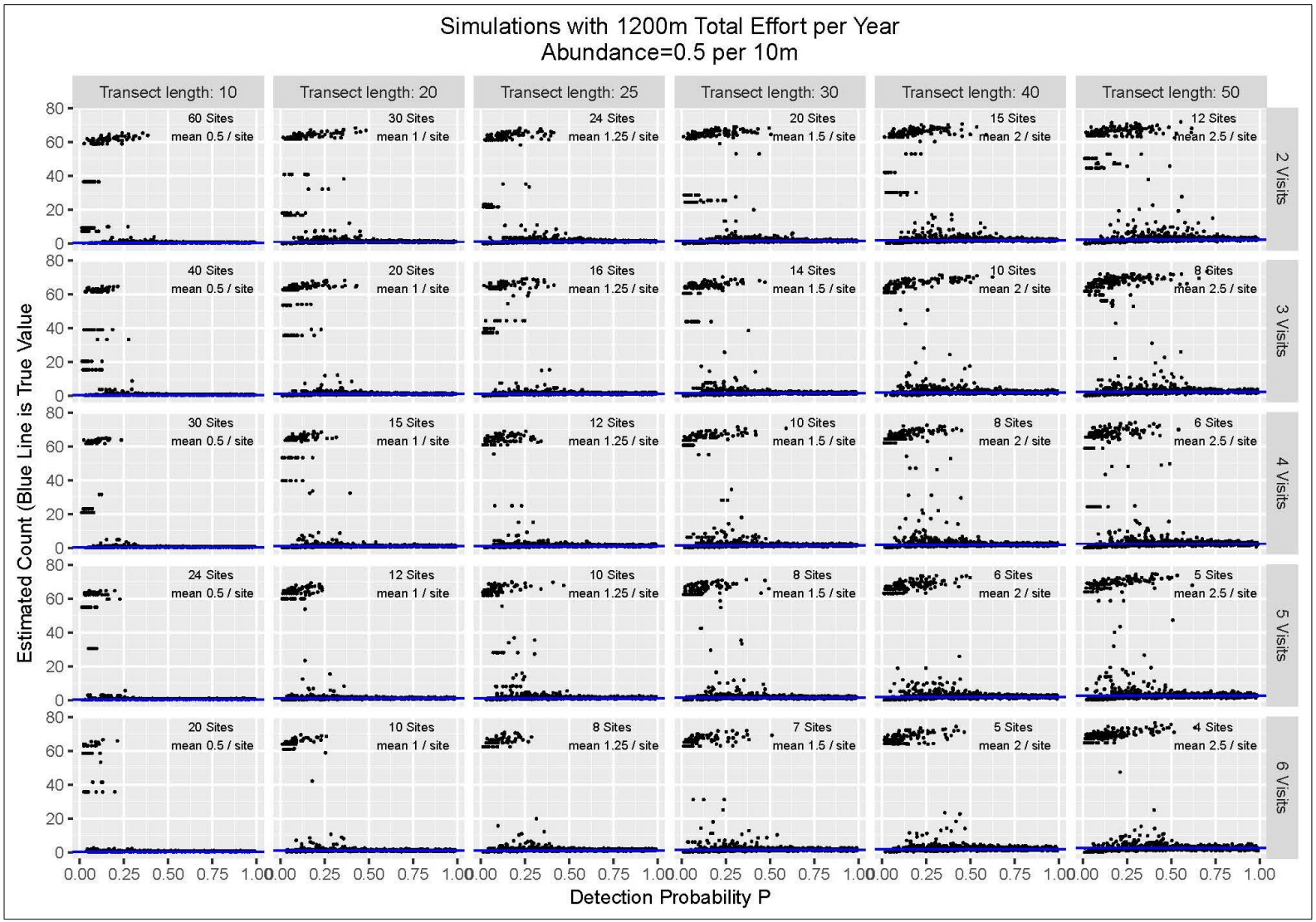


Figure A1-14. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 0.5 per 10 meters.

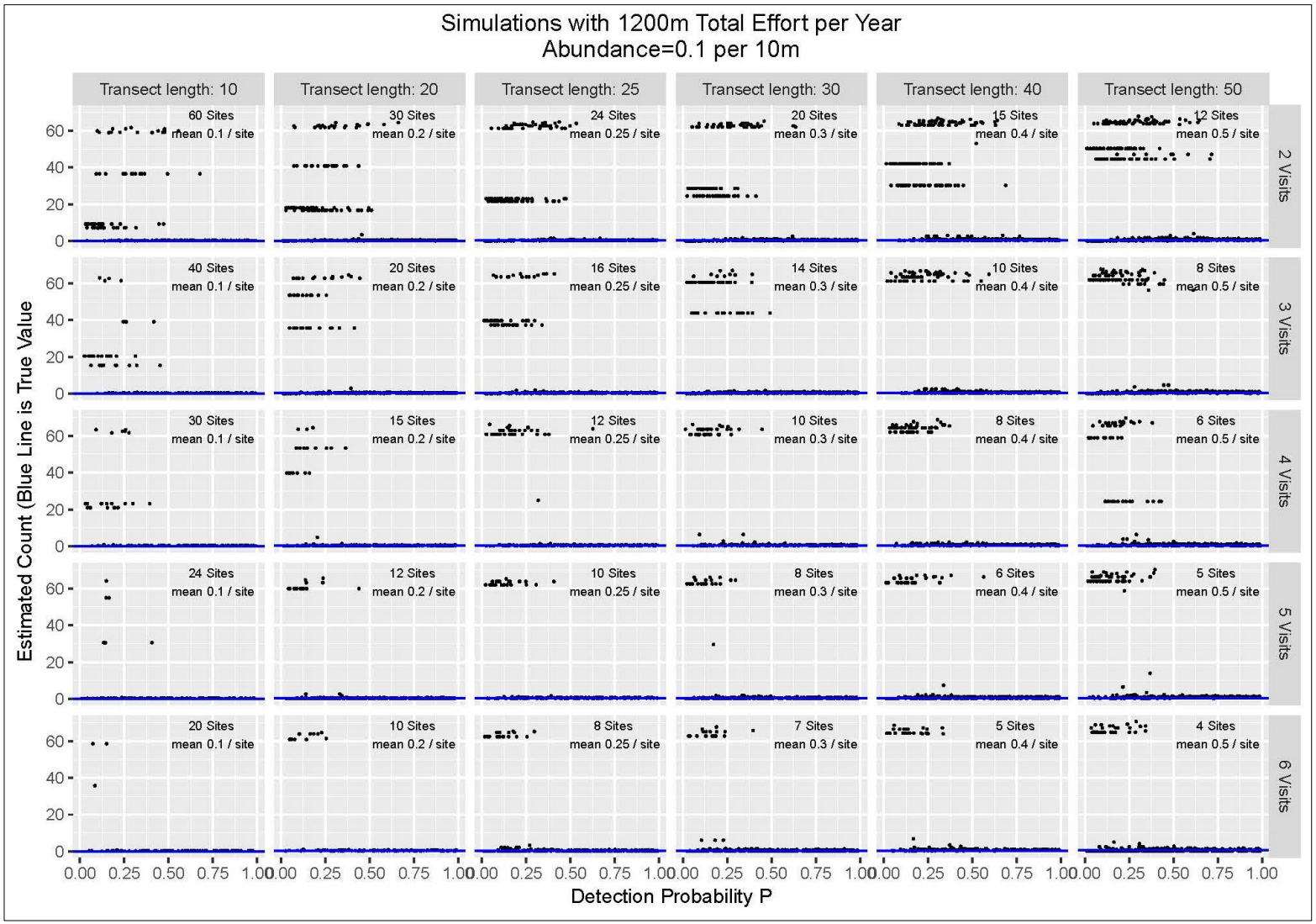


Figure A1-15. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability; Y axis is estimated abundance per transect. The blue line is the simulated value for average abundance per transect: the product of the abundance per meters times the transect length in meters. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 0.1 per 10 meters.

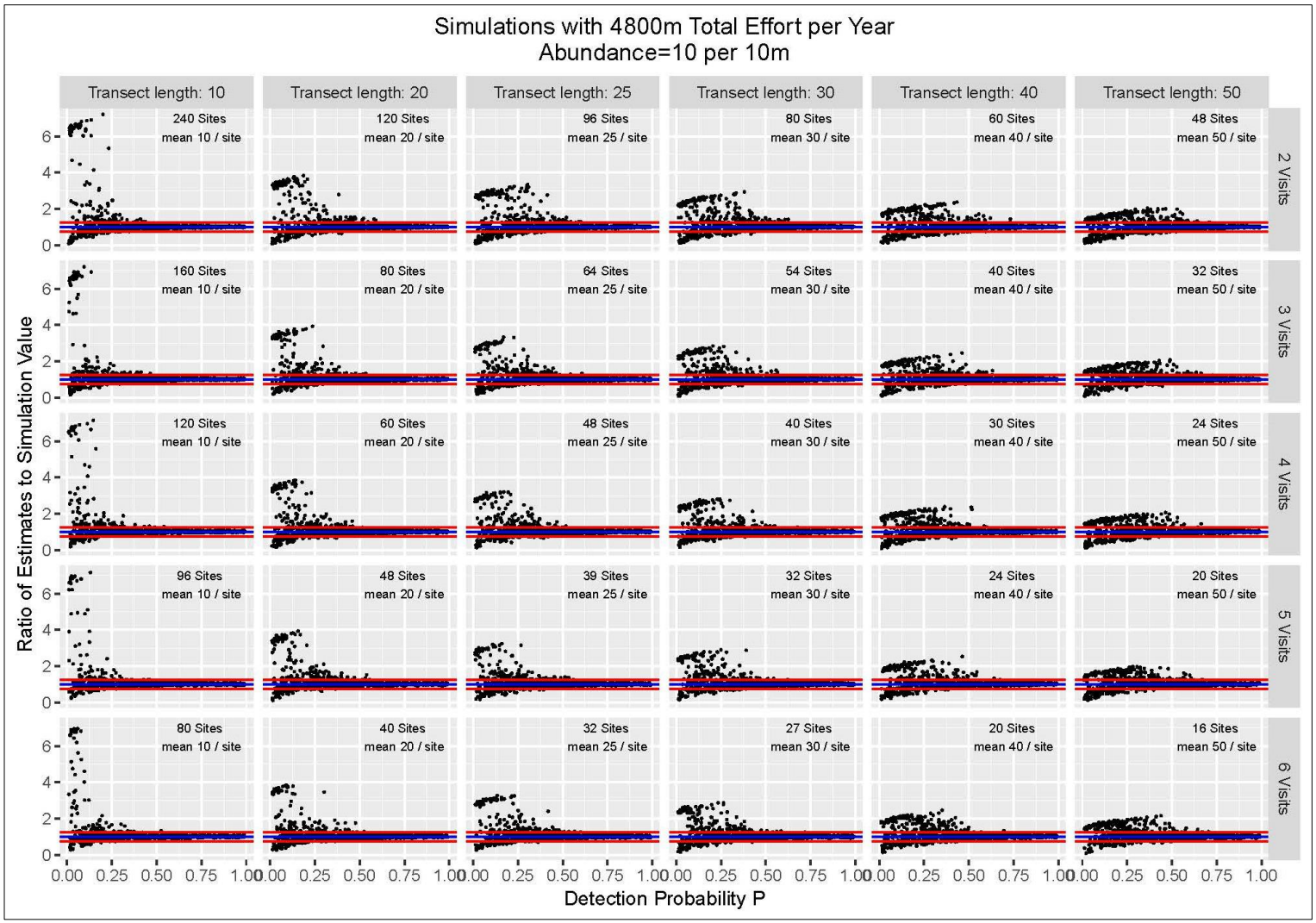


Figure A2-1. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 10 per 10 meters (32.8 ft).

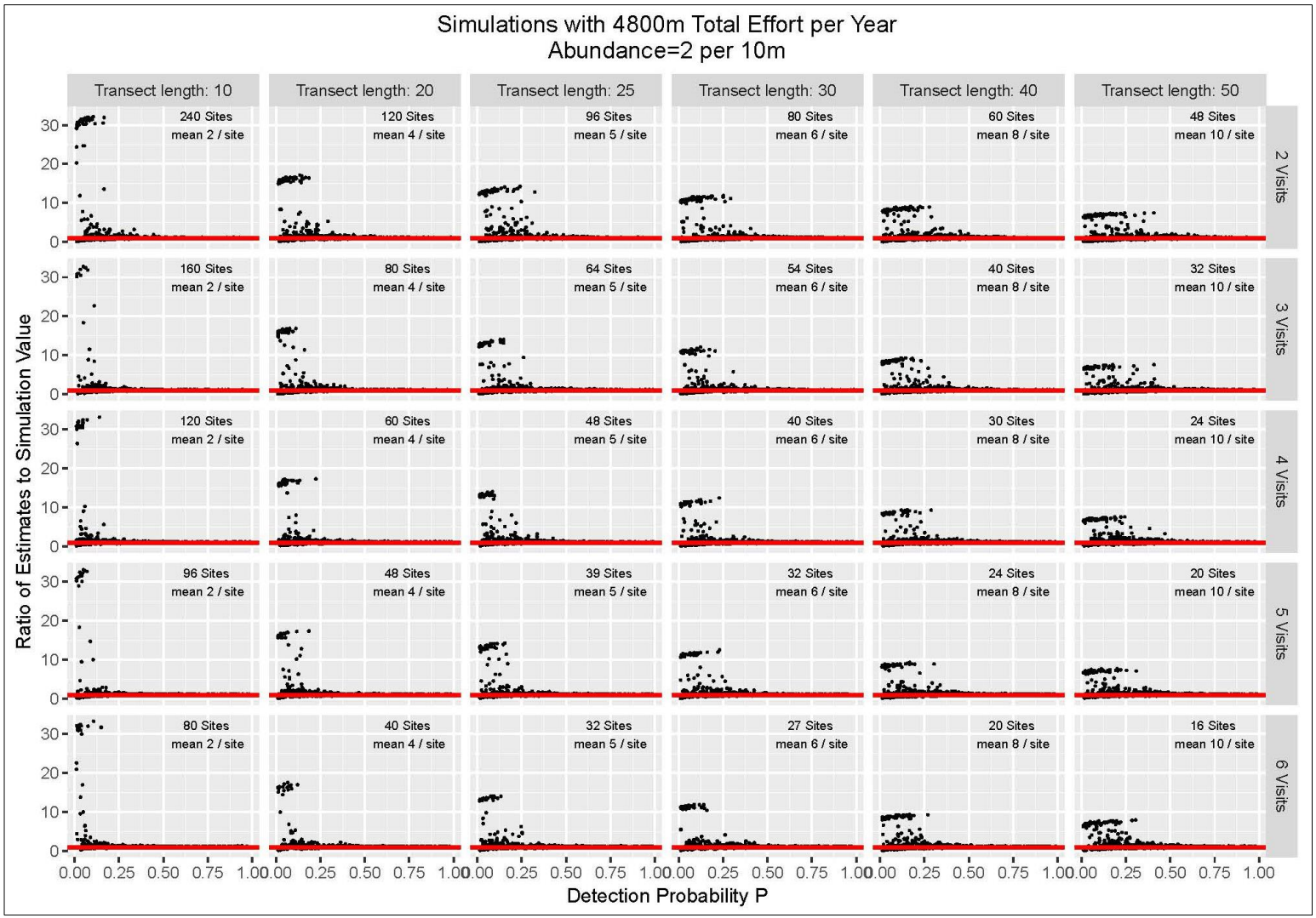


Figure A2-2. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 2 per 10 meters (32.8 ft).

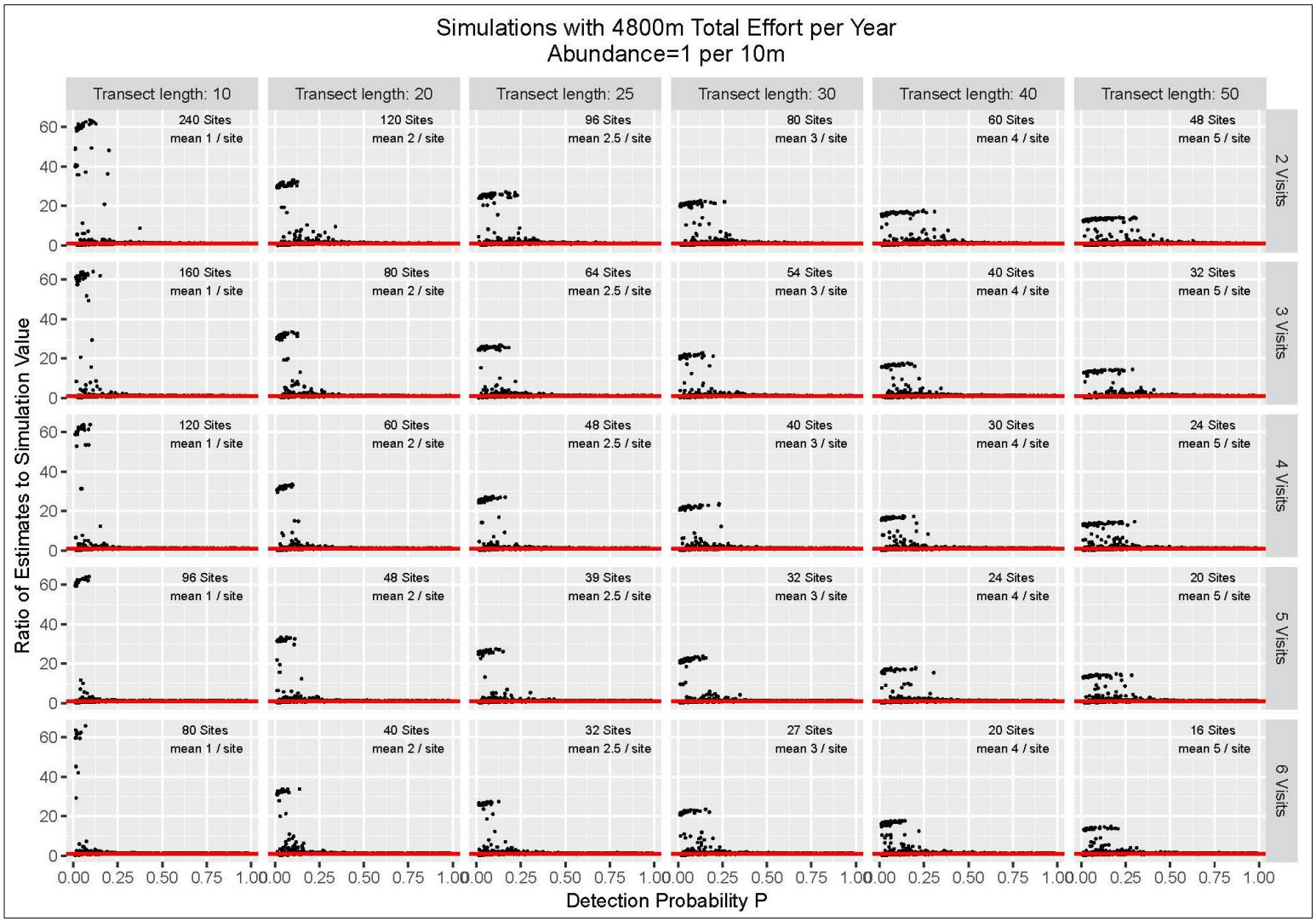


Figure A2-3. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 1 per 10 meters (32.8 ft).

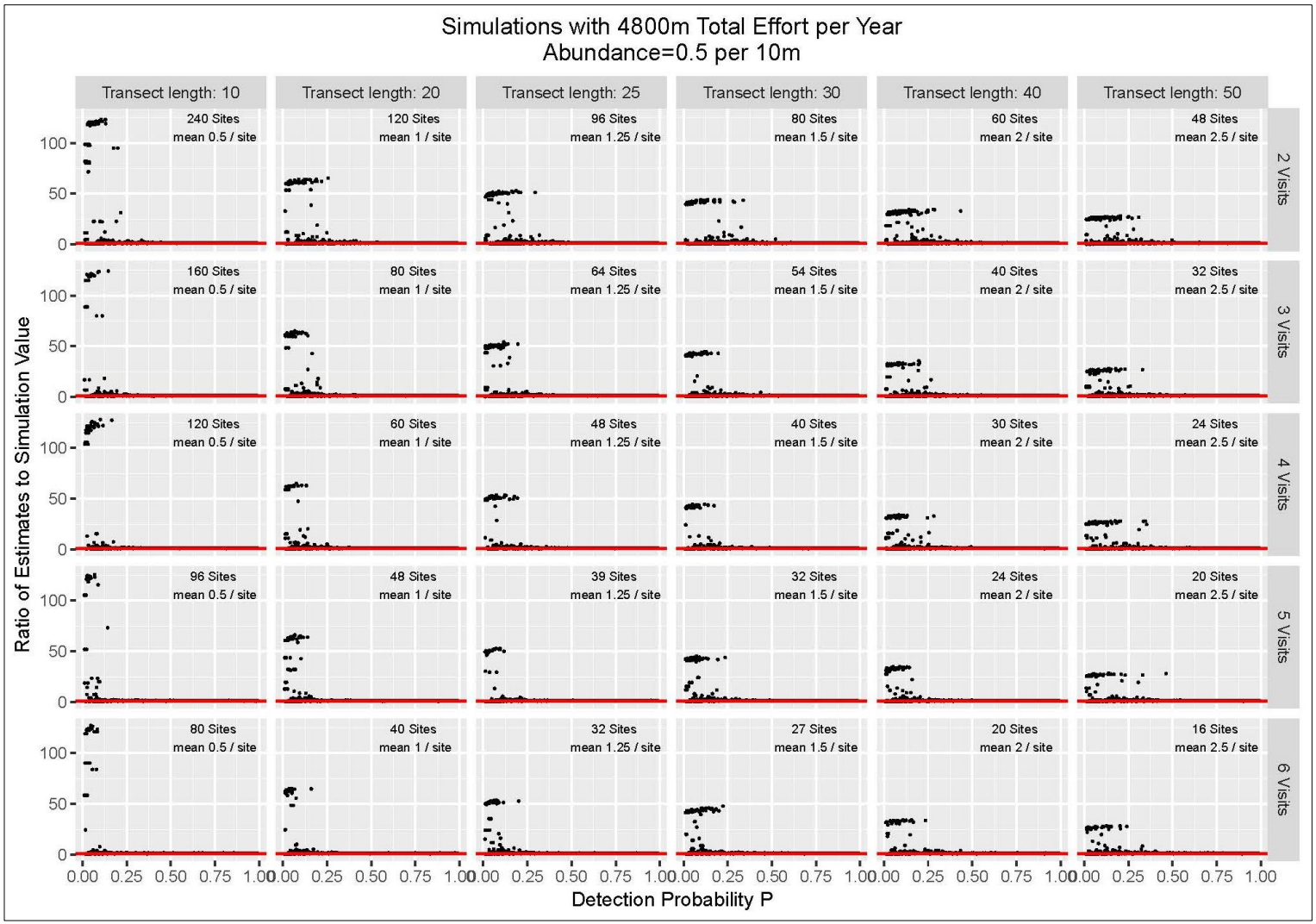


Figure A2-4. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 0.5 per 10 meters (32.8 ft).

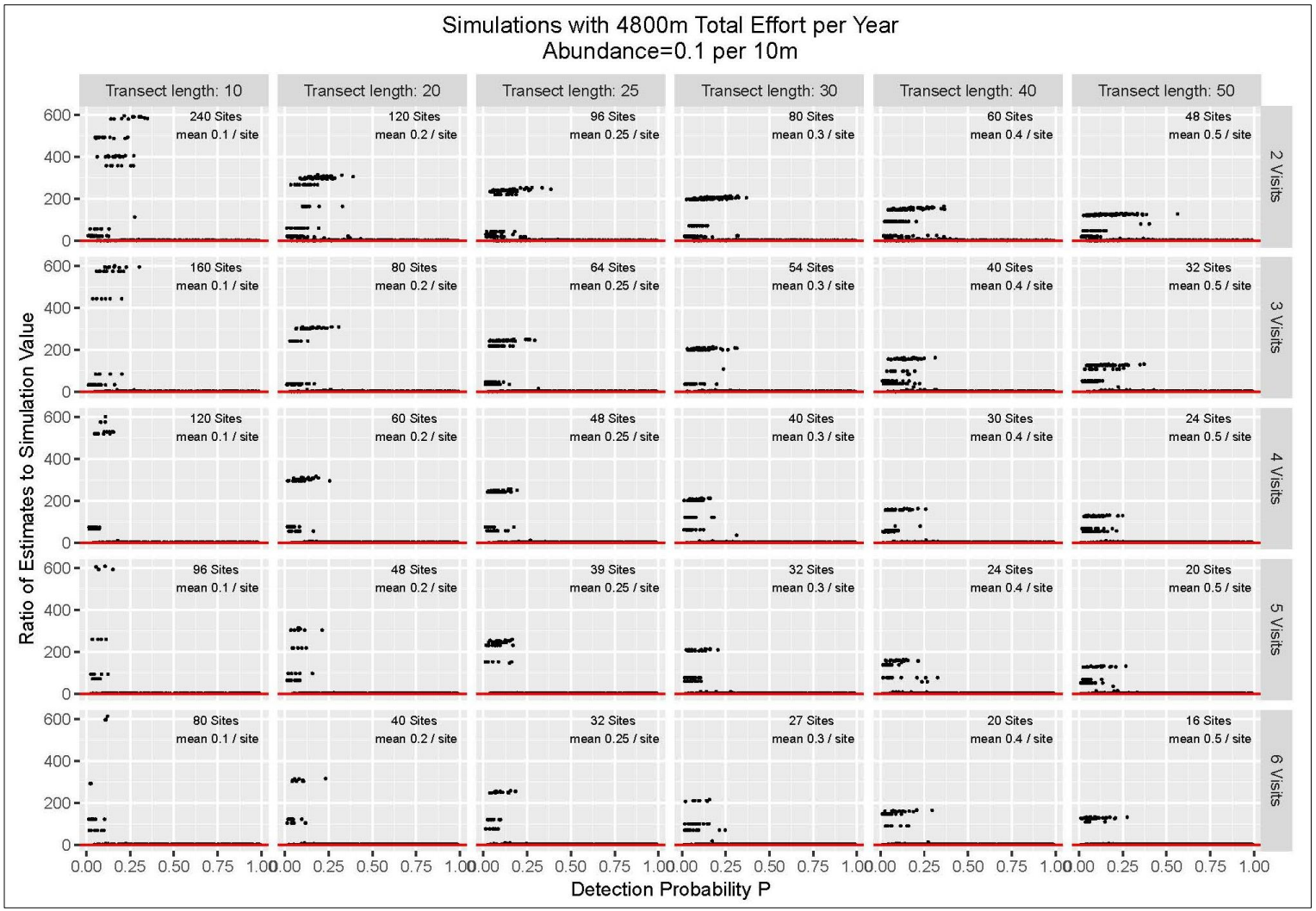


Figure A2-5. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 0.1 per 10 meters (32.8 ft).

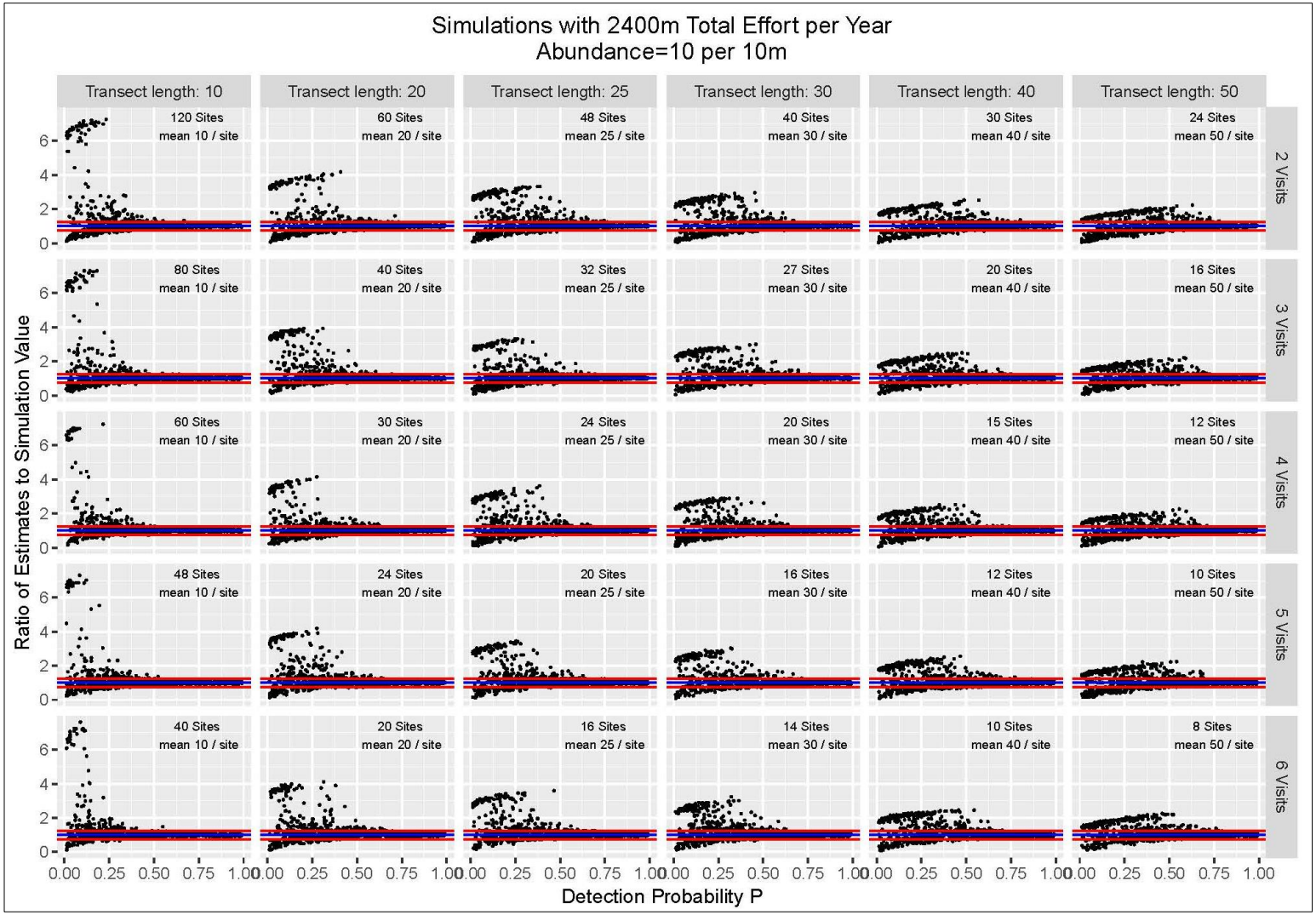


Figure A2-6. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 10 per 10 meters (32.8 ft).

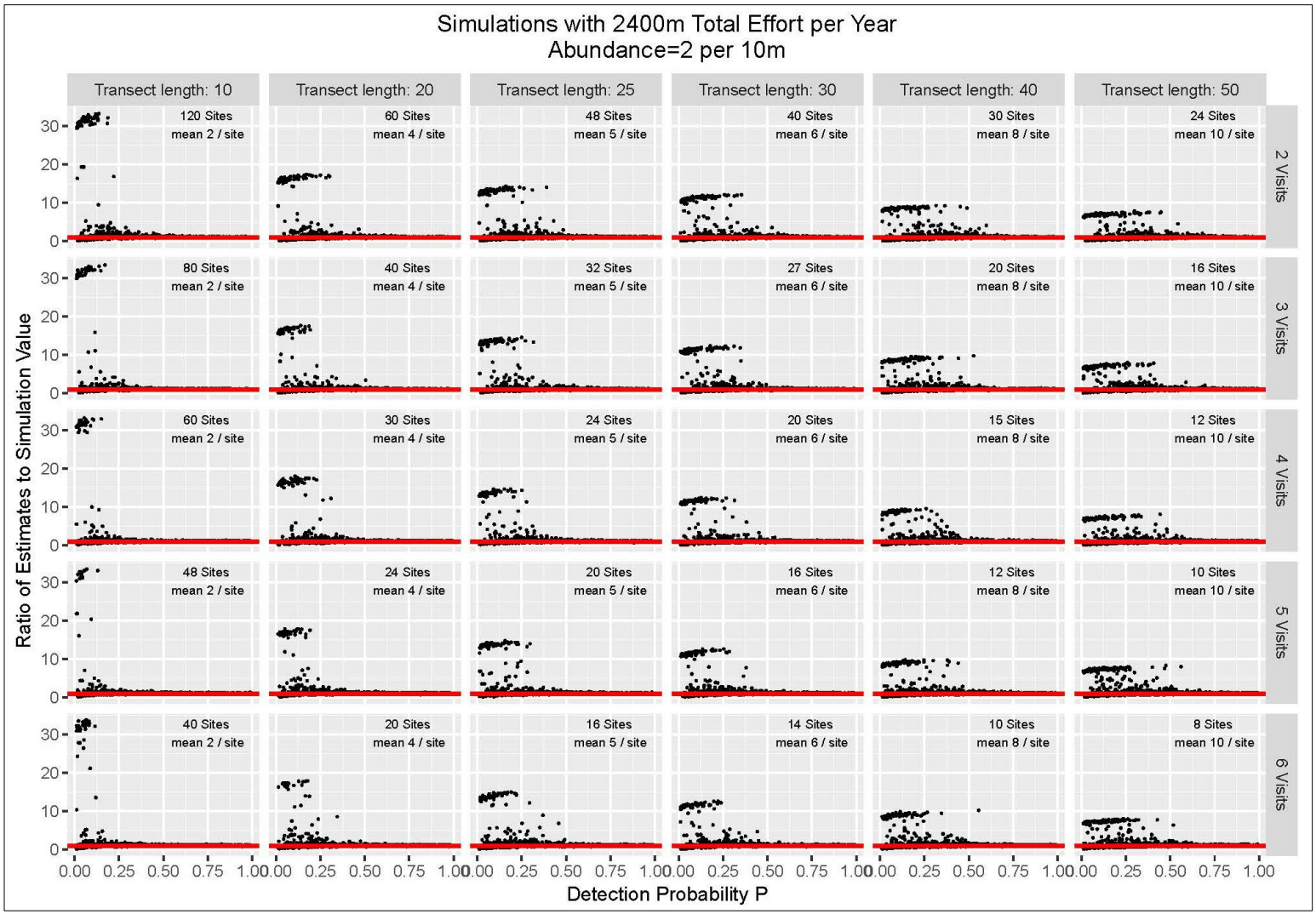


Figure A2-7. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 2 per 10 meters (32.8 ft).

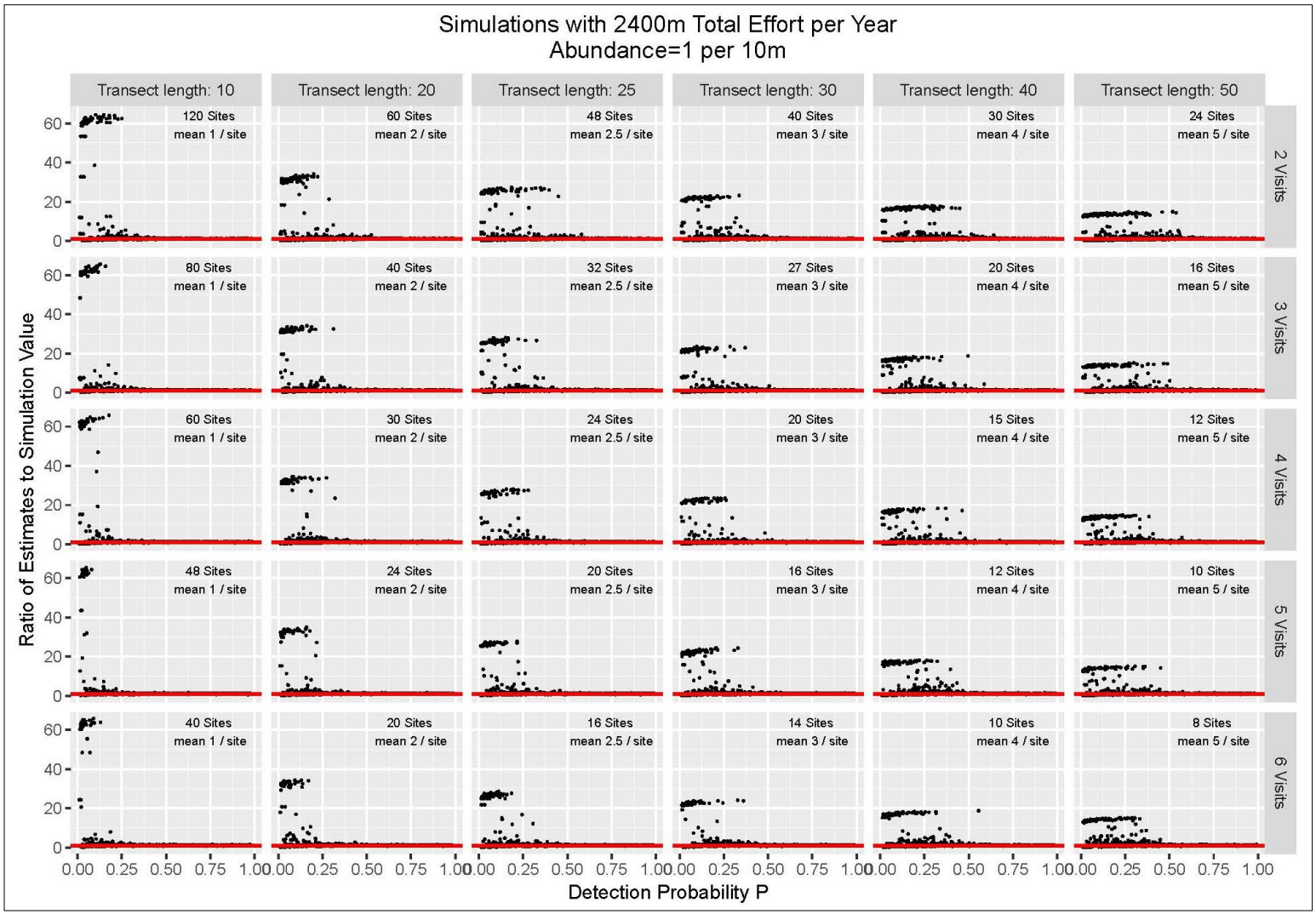


Figure A2-8. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 1 per 10 meters (32.8 ft).

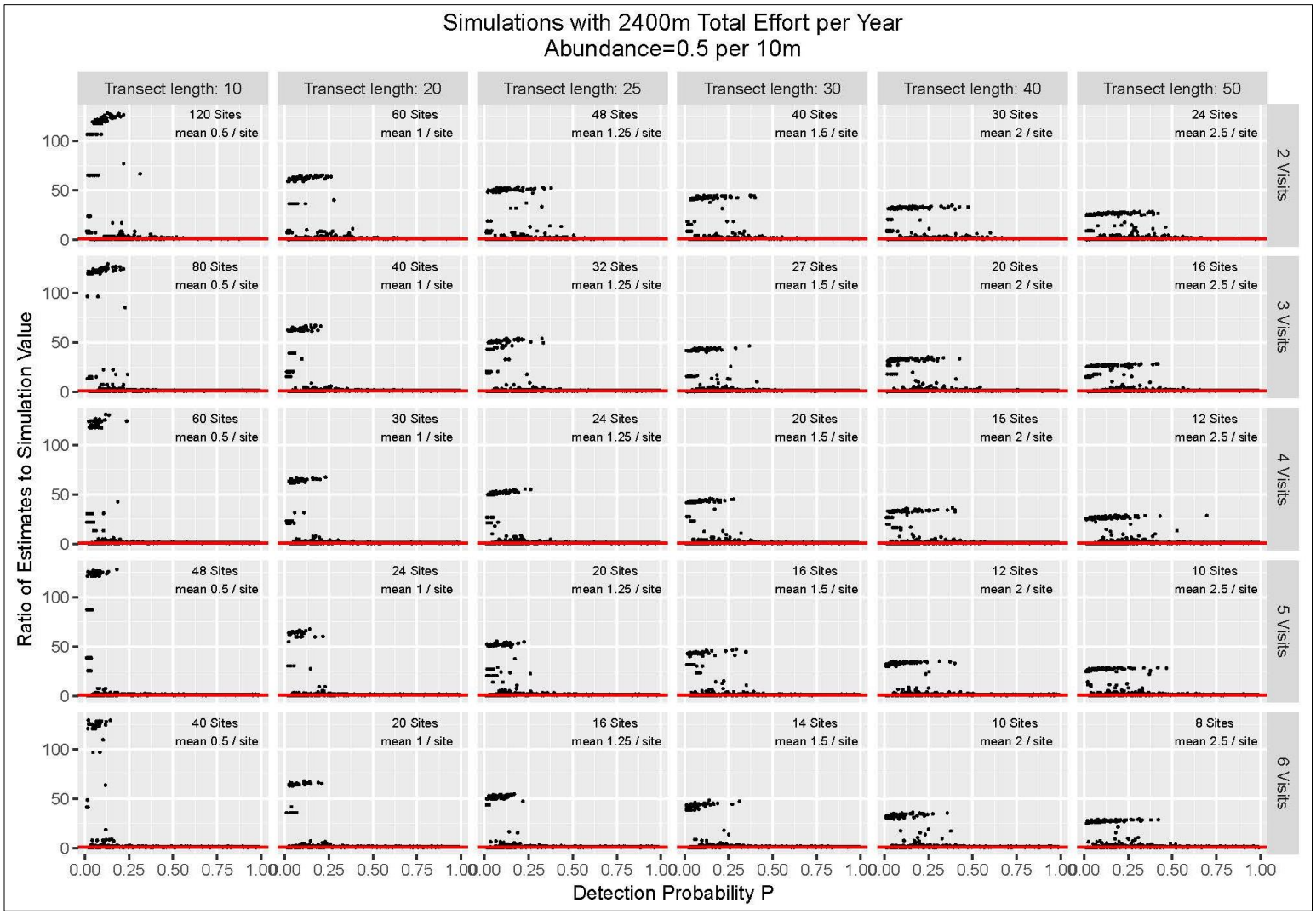


Figure A2-9. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 0.5 per 10 meters (32.8 ft).

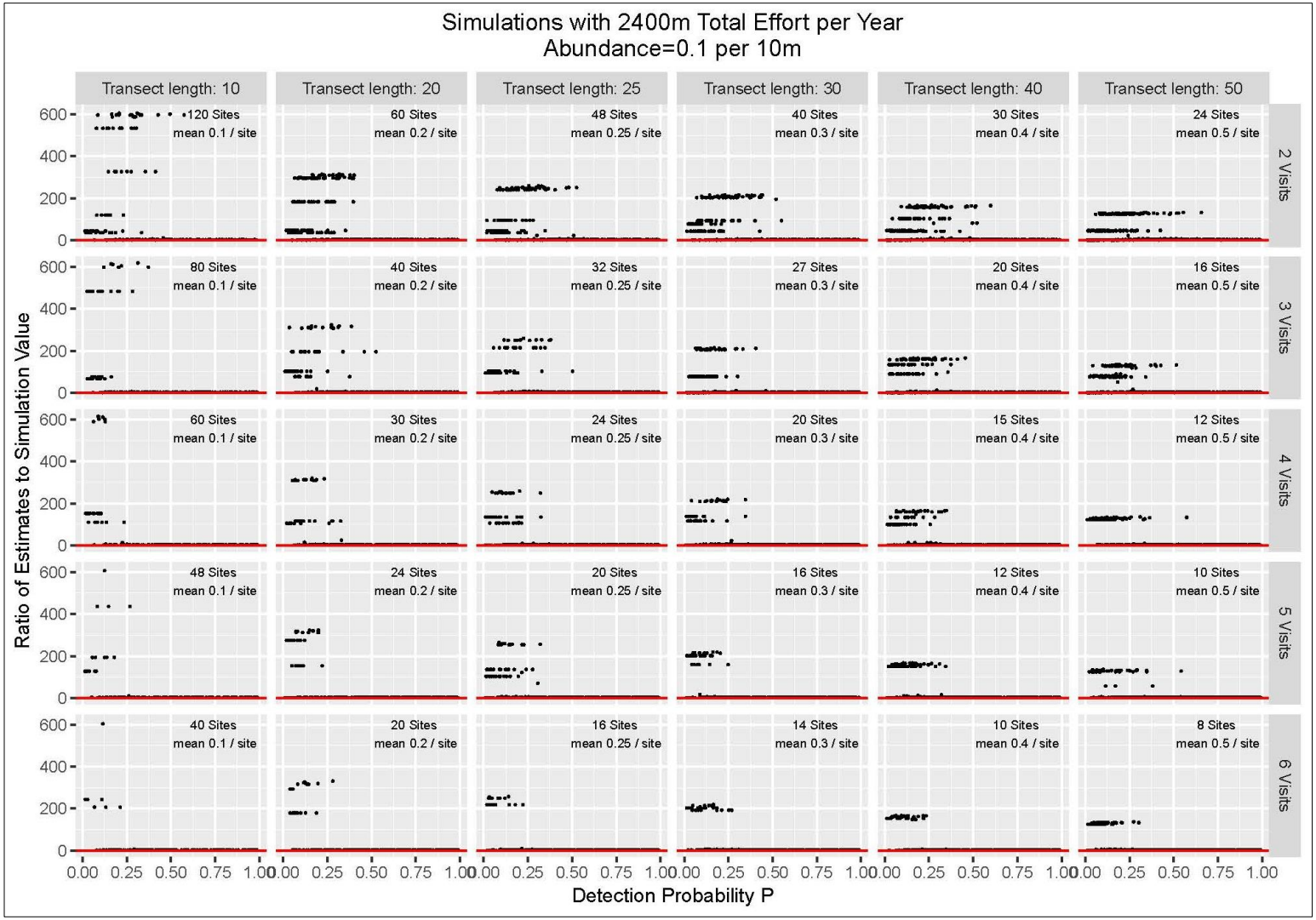


Figure A2-10. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 0.1 per 10 meters (32.8 ft).

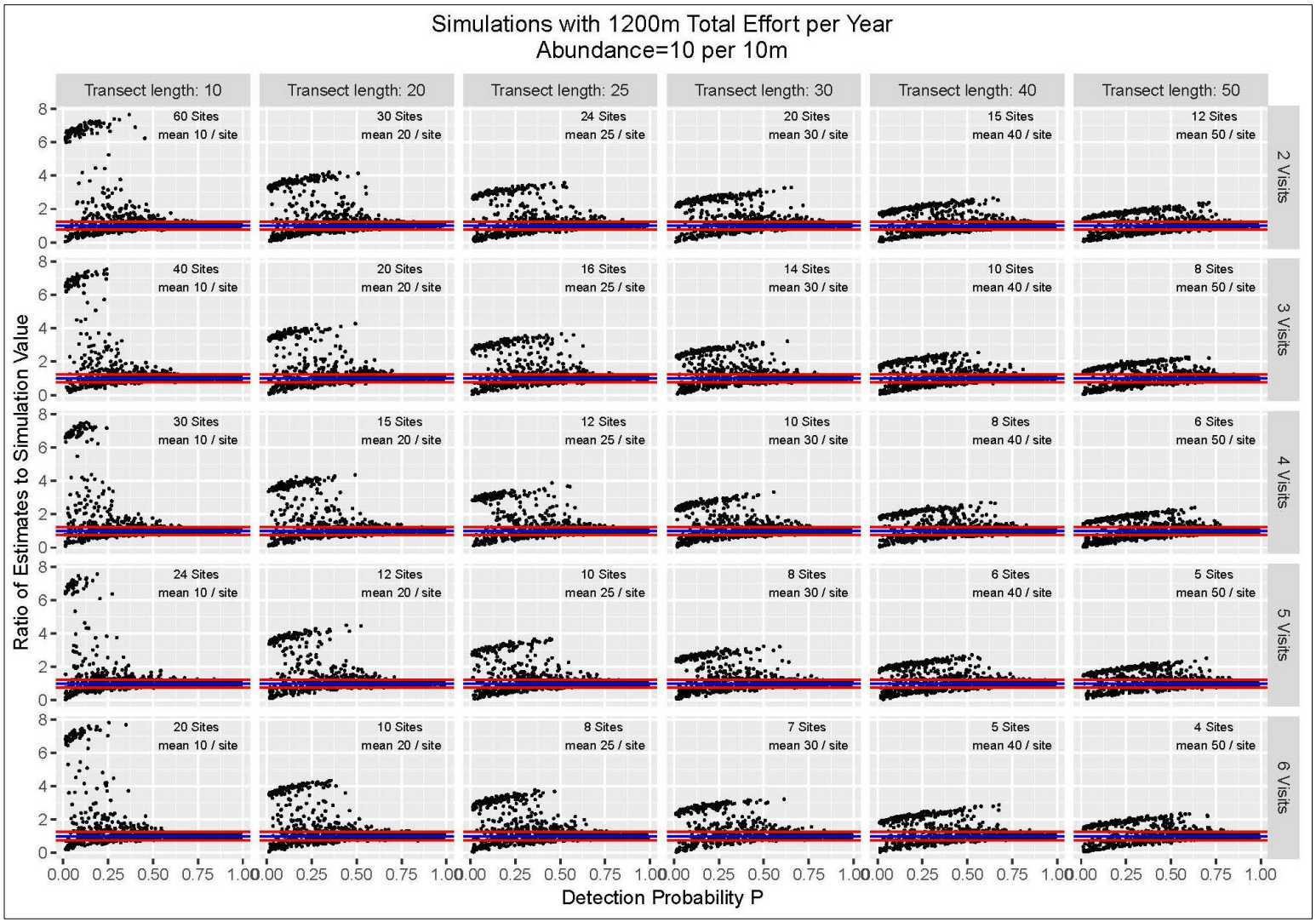


Figure A2-11. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 10 per 10 meters (32.8 ft).

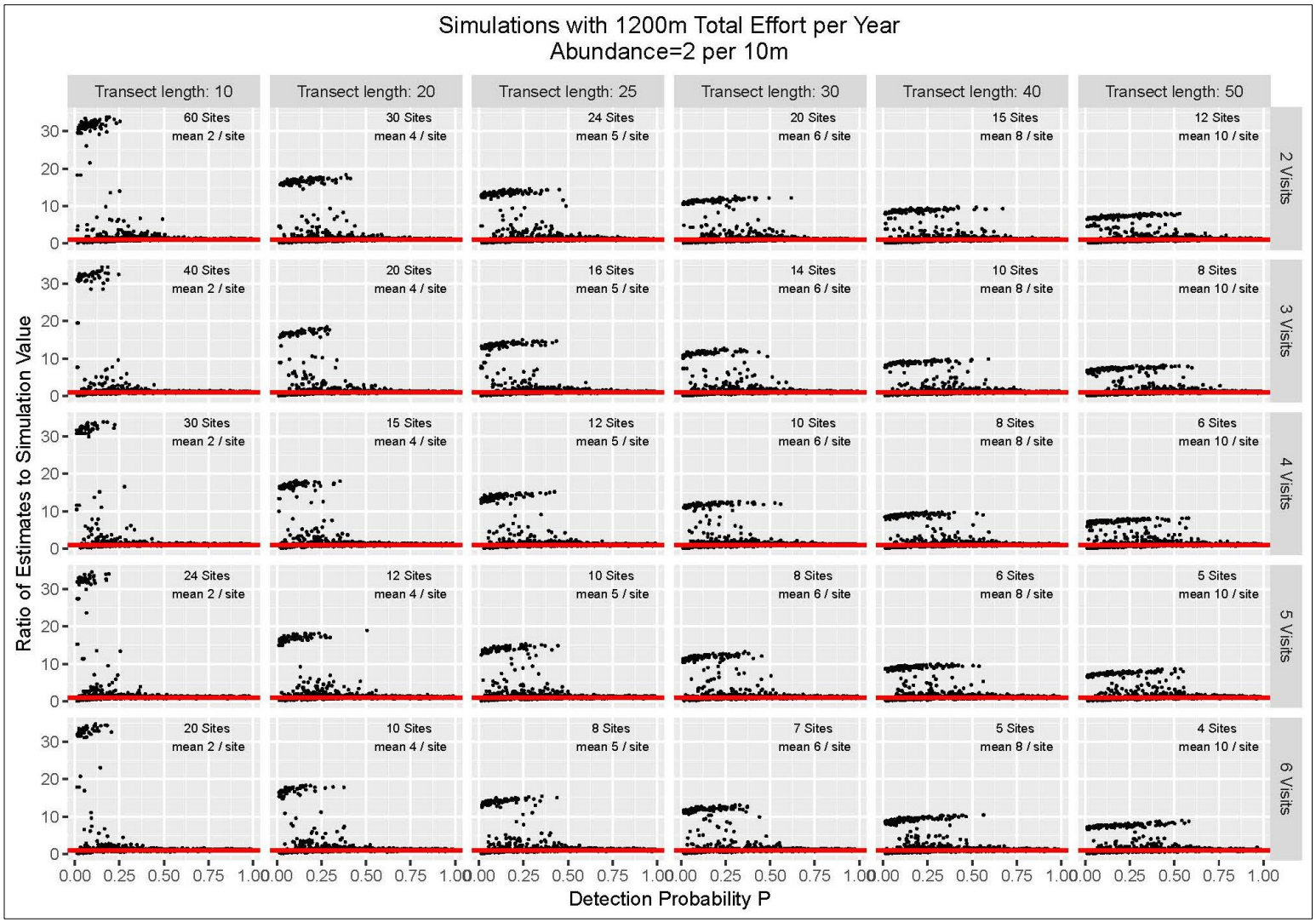


Figure A2-12. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 2 per 10 meters (32.8 ft).

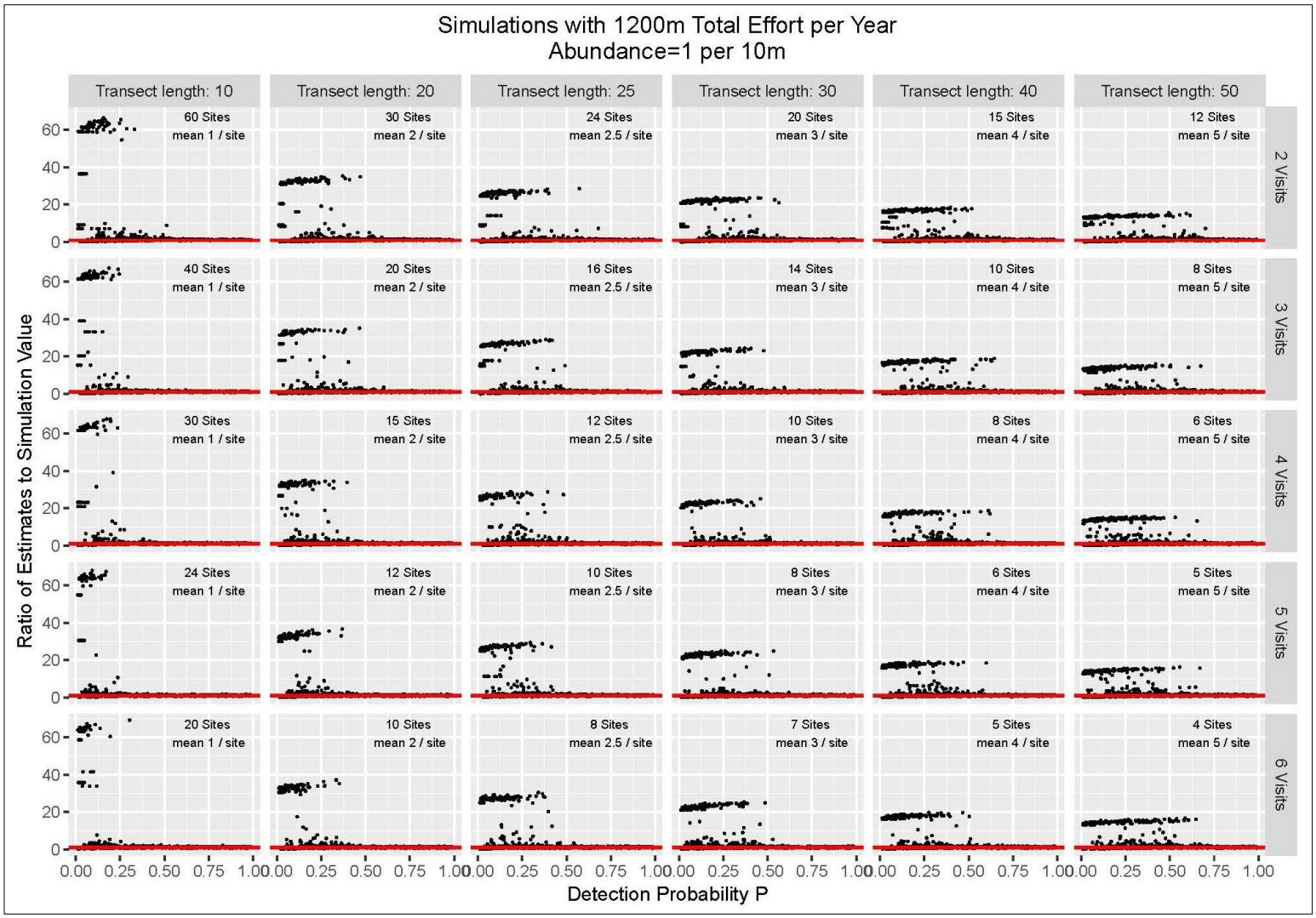


Figure A2-13. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 1 per 10 meters (32.8 ft).

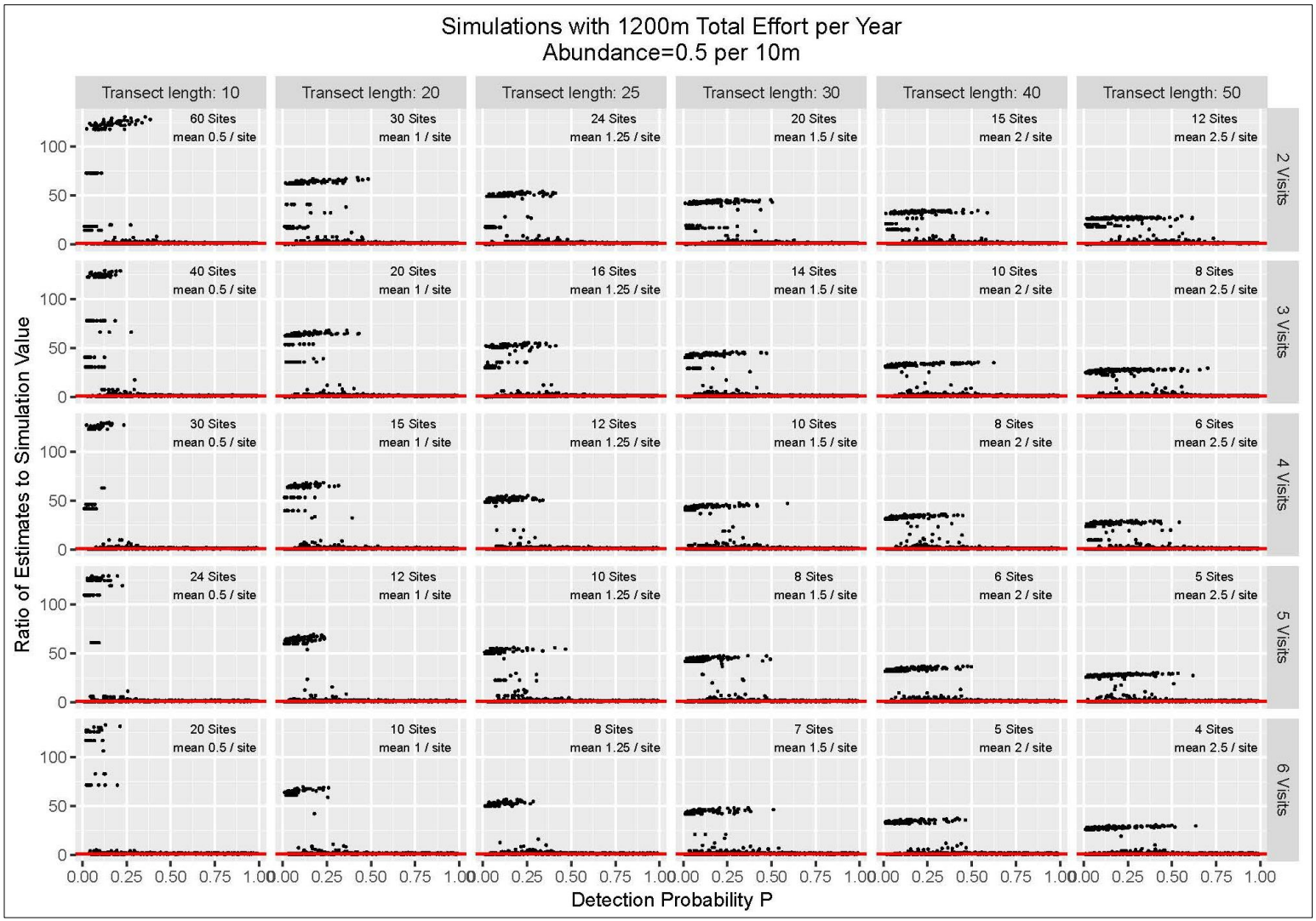


Figure A2-14. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 0.5 per 10 meters (32.8 ft).

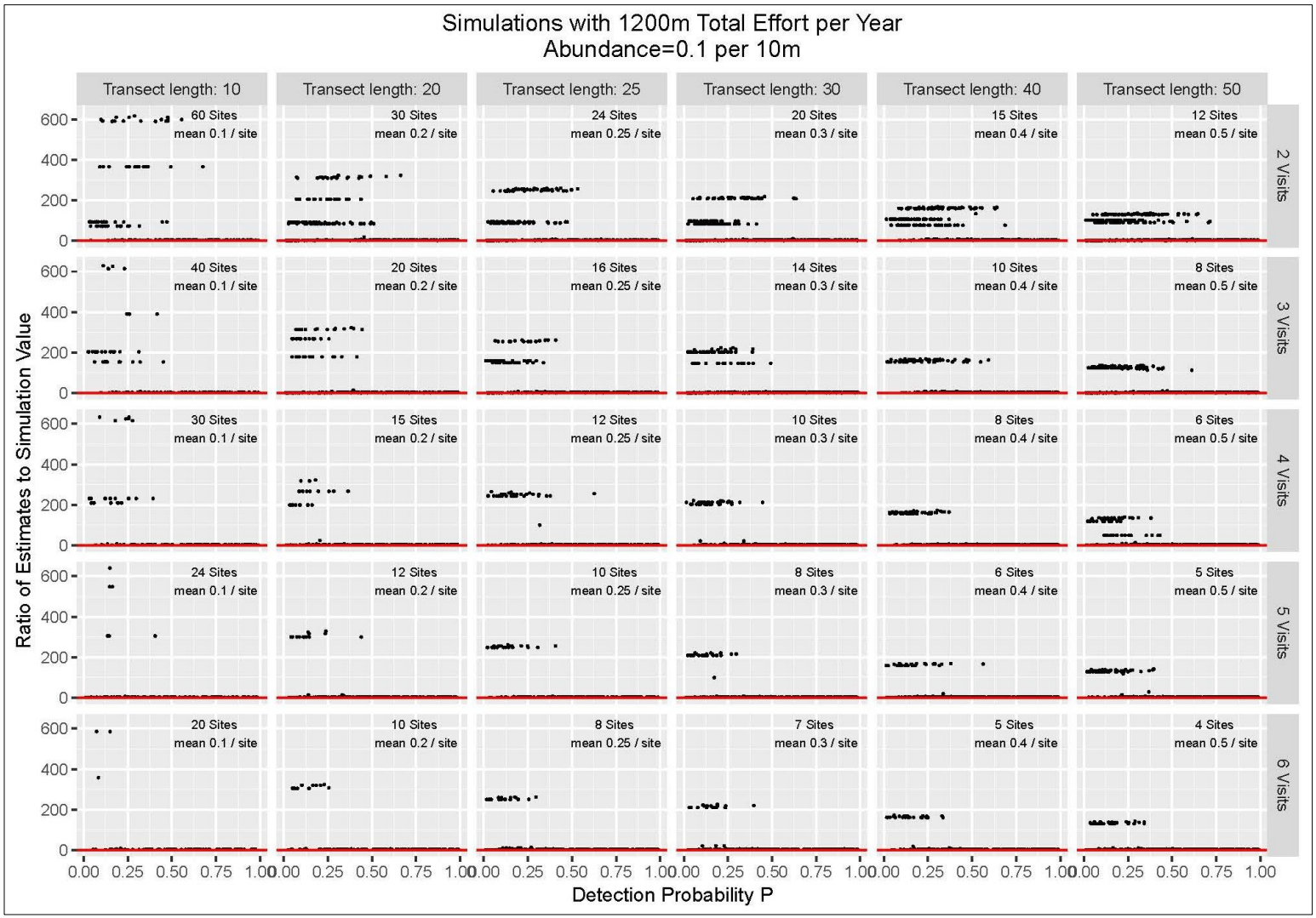


Figure A2-15. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. The estimate on the Y axis is expressed as the ratio of the estimated abundance per transect to the expected abundance per transect, so 1 is an accurate estimate. The horizontal blue line is the expected value of 1; the red horizontal lines indicate estimates 25% above or below the true value. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 0.1 per 10 meters (32.8 ft).

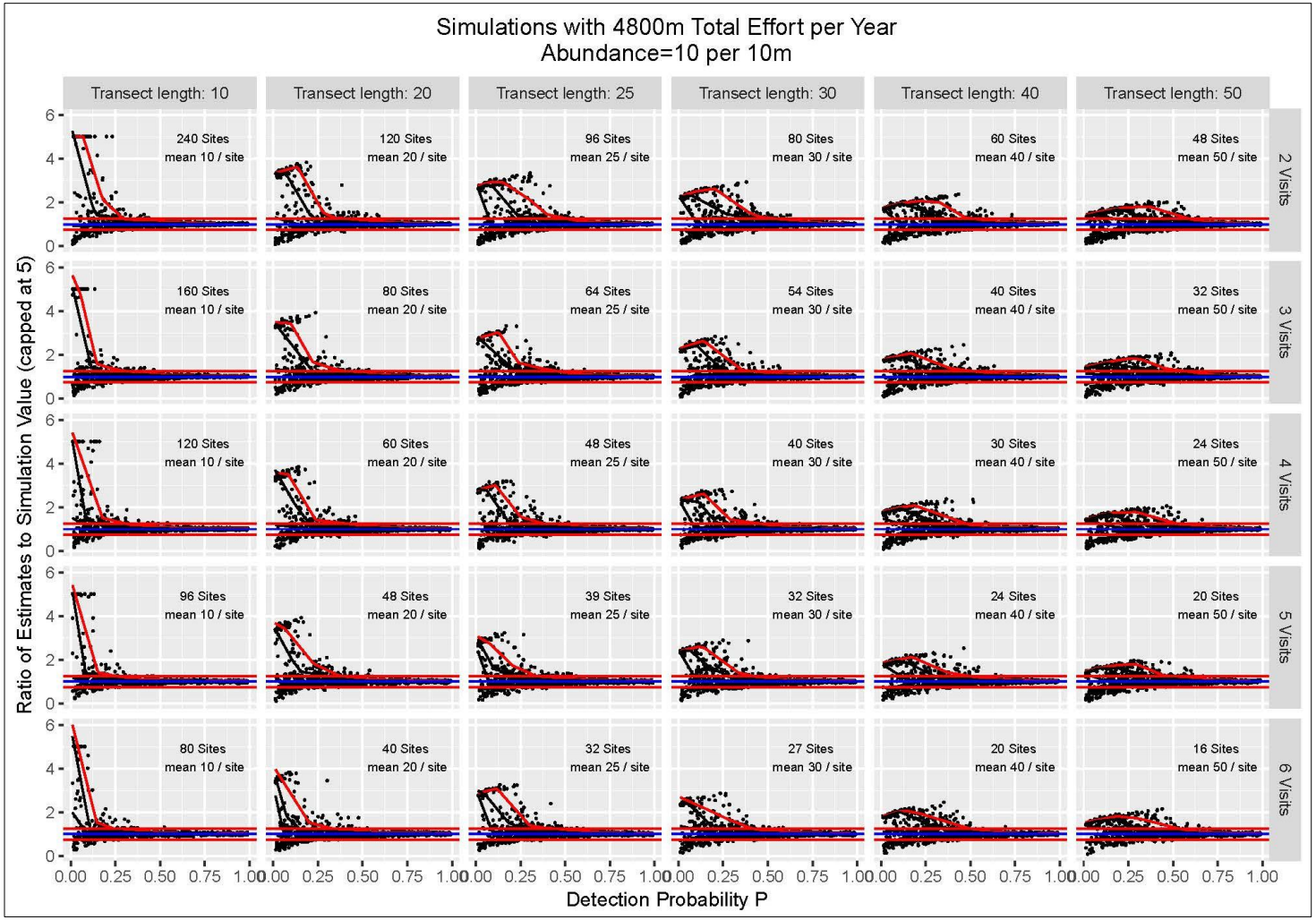


Figure A3-1. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The three curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 10 per 10 meters (32.8 ft).

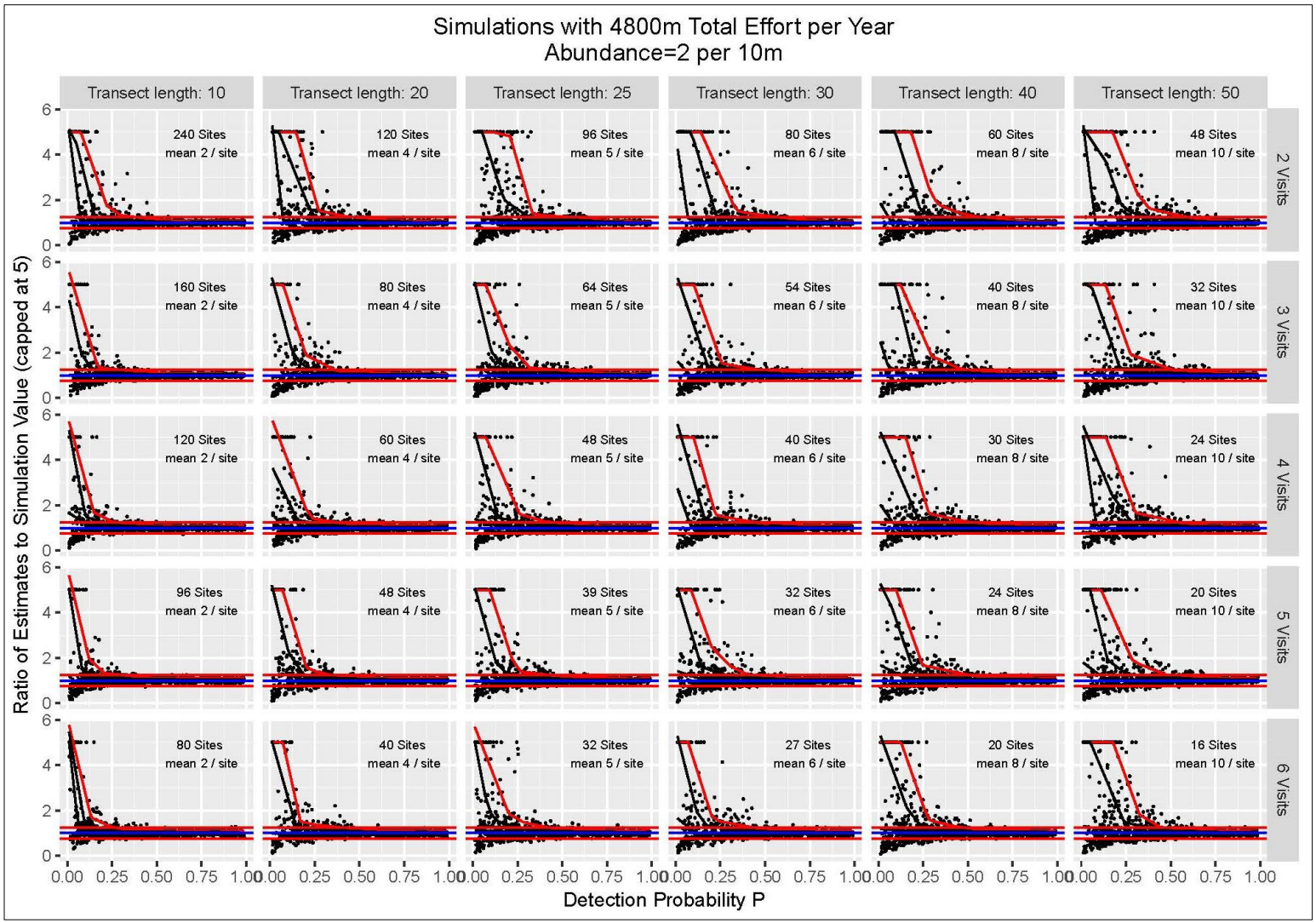


Figure A3-2. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The three curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 2 per 10 meters (32.8 ft).

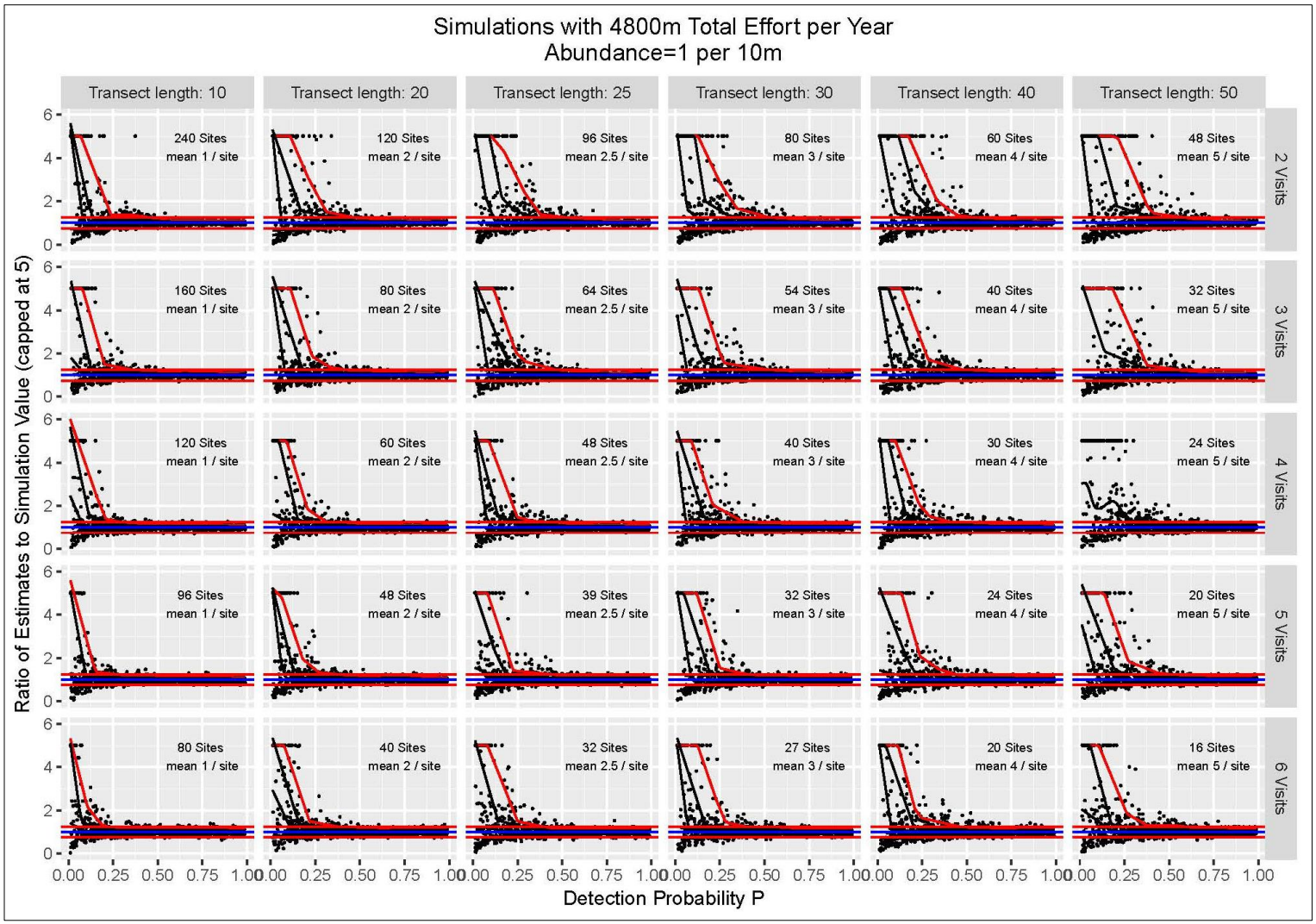


Figure A3-3. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 1 per 10 meters (32.8 ft).

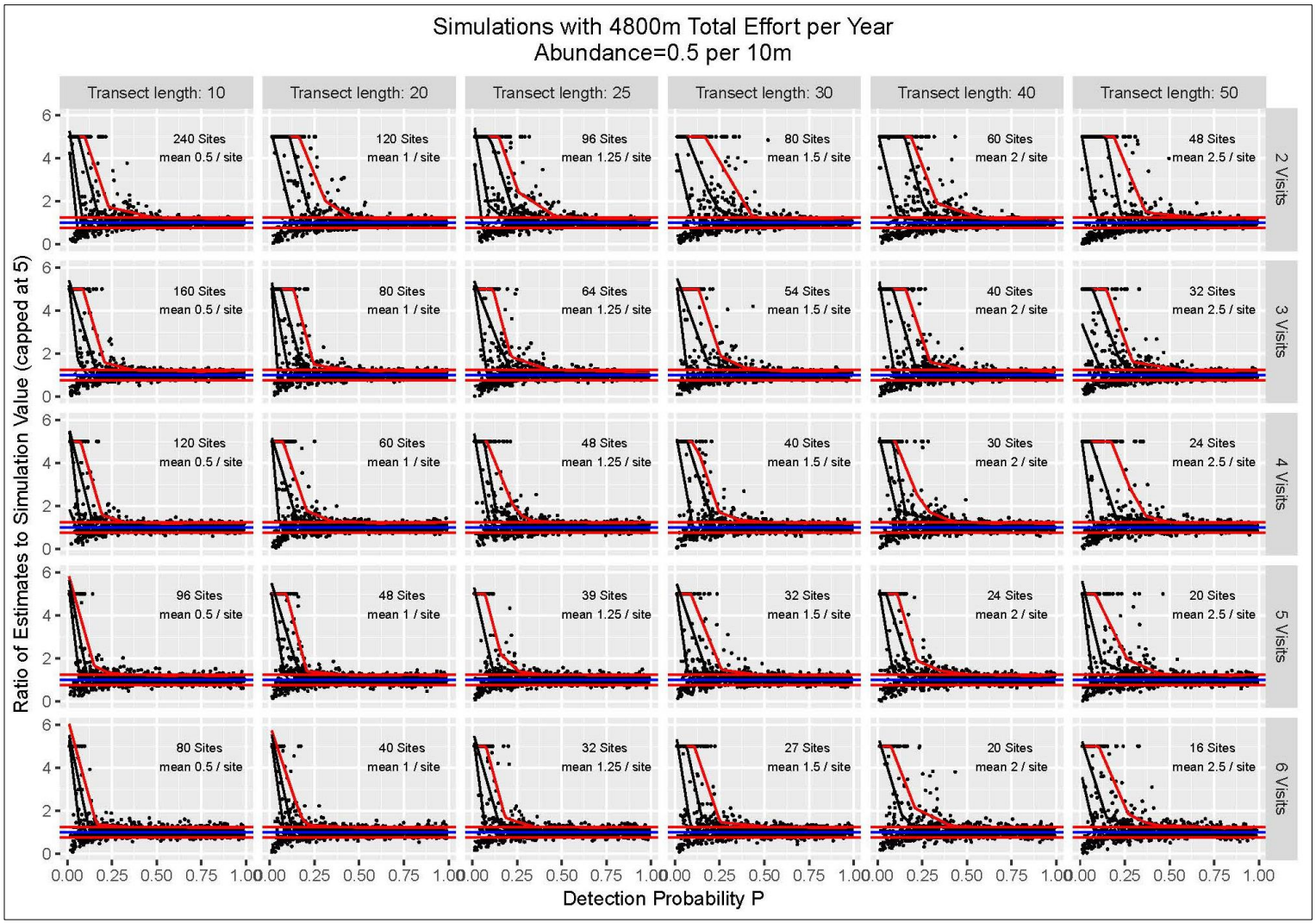


Figure A3-4. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 0.5 per 10 meters (32.8 ft).

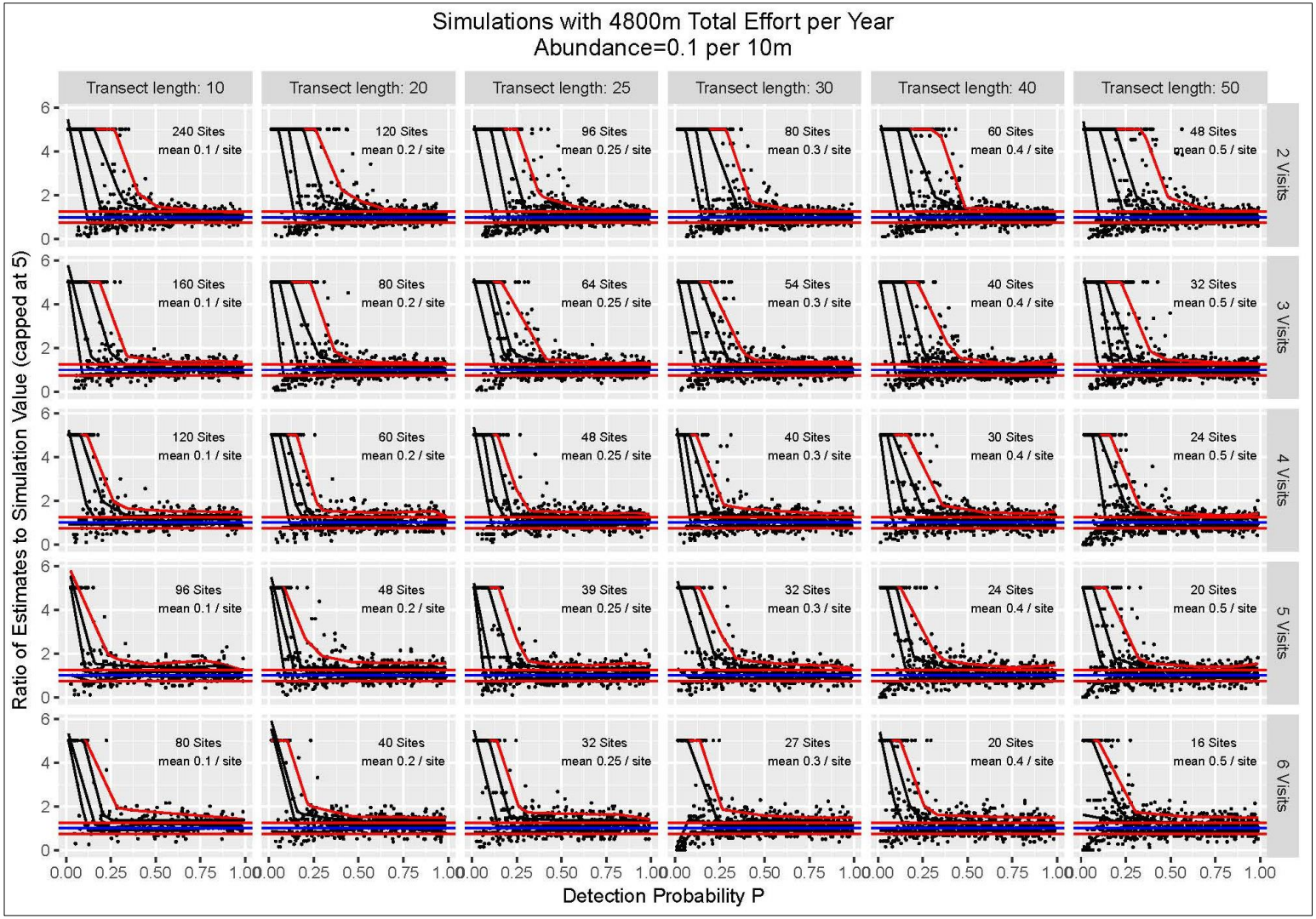


Figure A3-5. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 4,800 meters Total Effort per Year. Abundance equals 0.1 per 10 meters (32.8 ft).

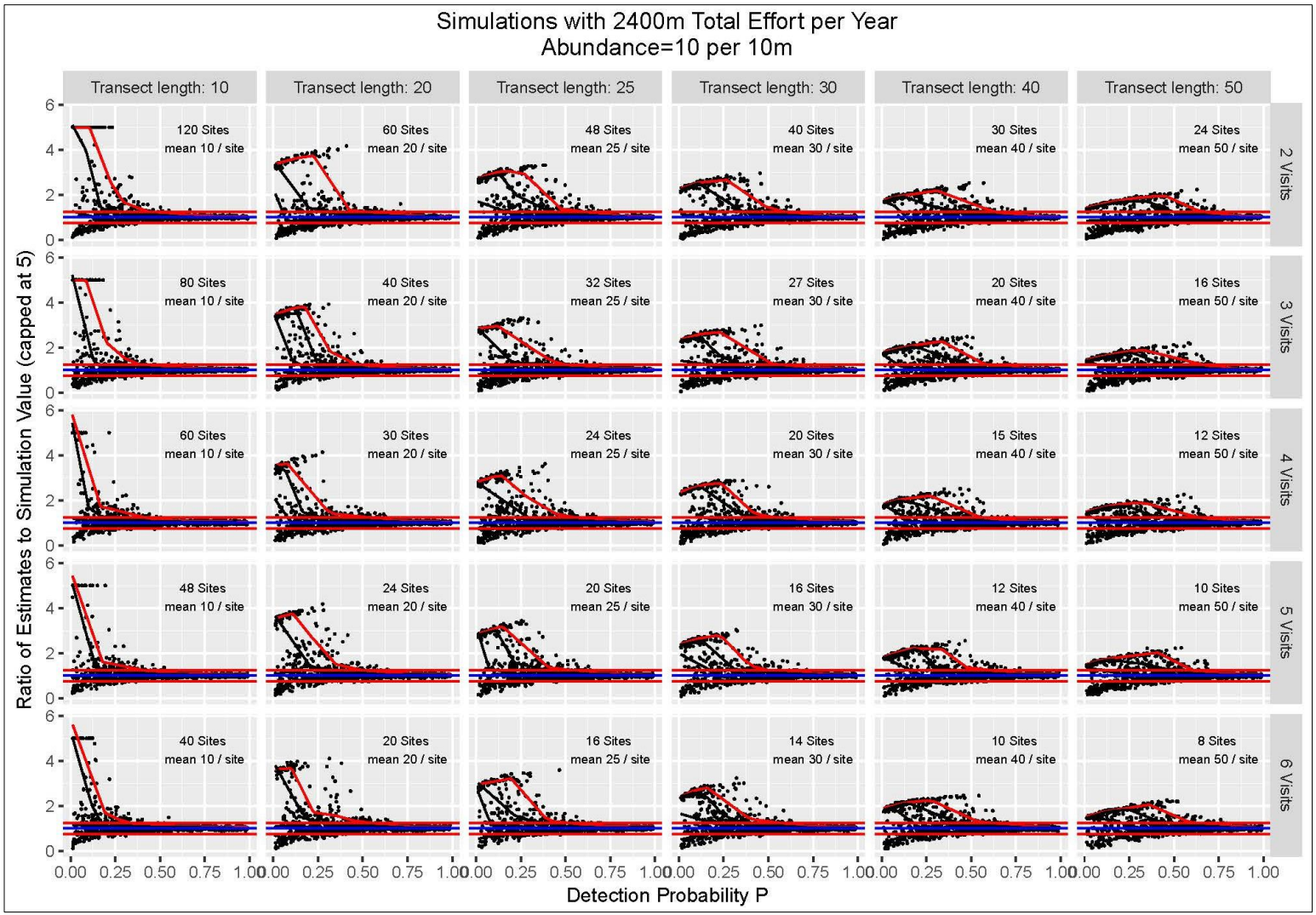


Figure A3-6. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 10 per 10 meters (32.8 ft).

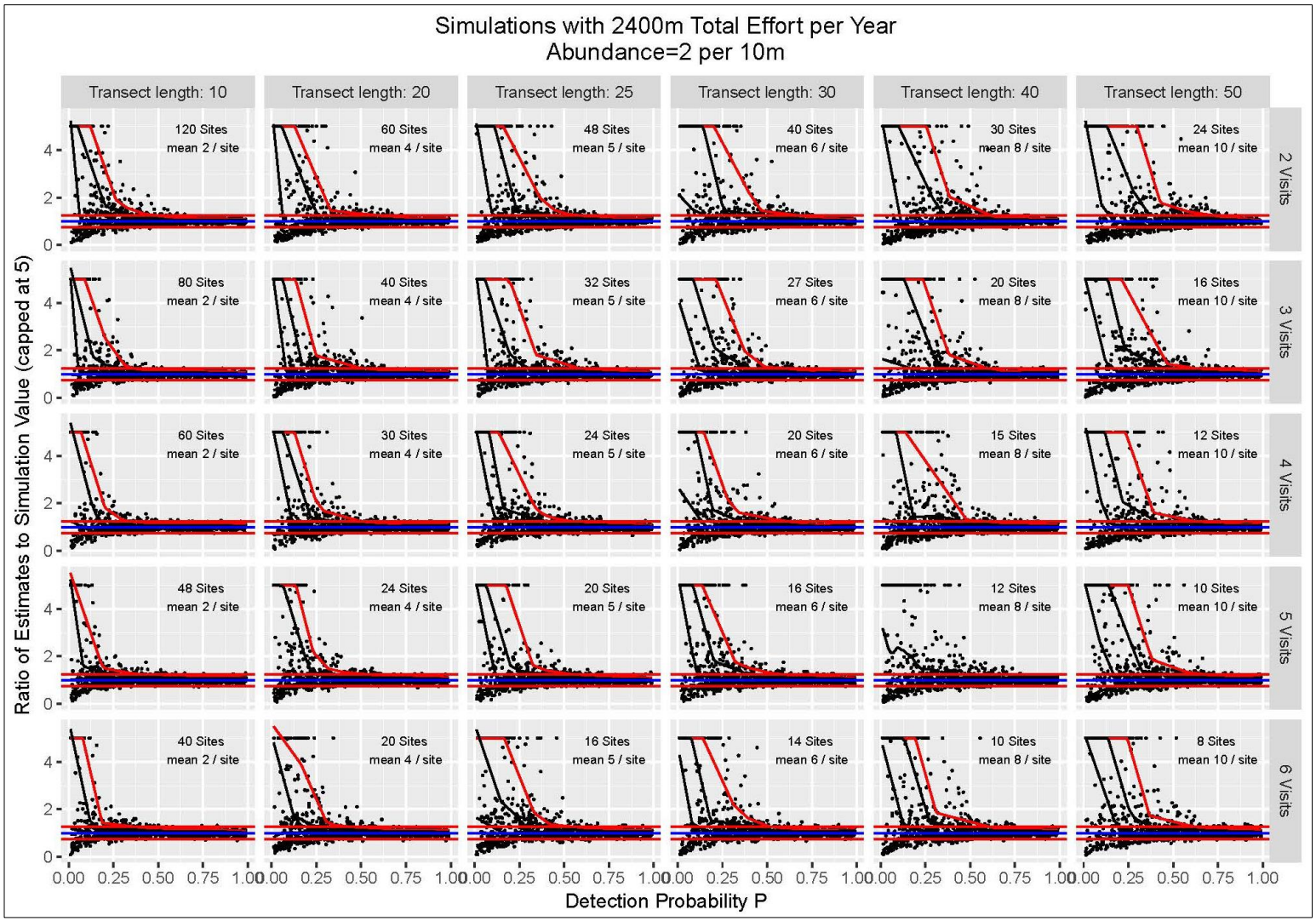


Figure A3-7. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 2 per 10 meters (32.8 ft).

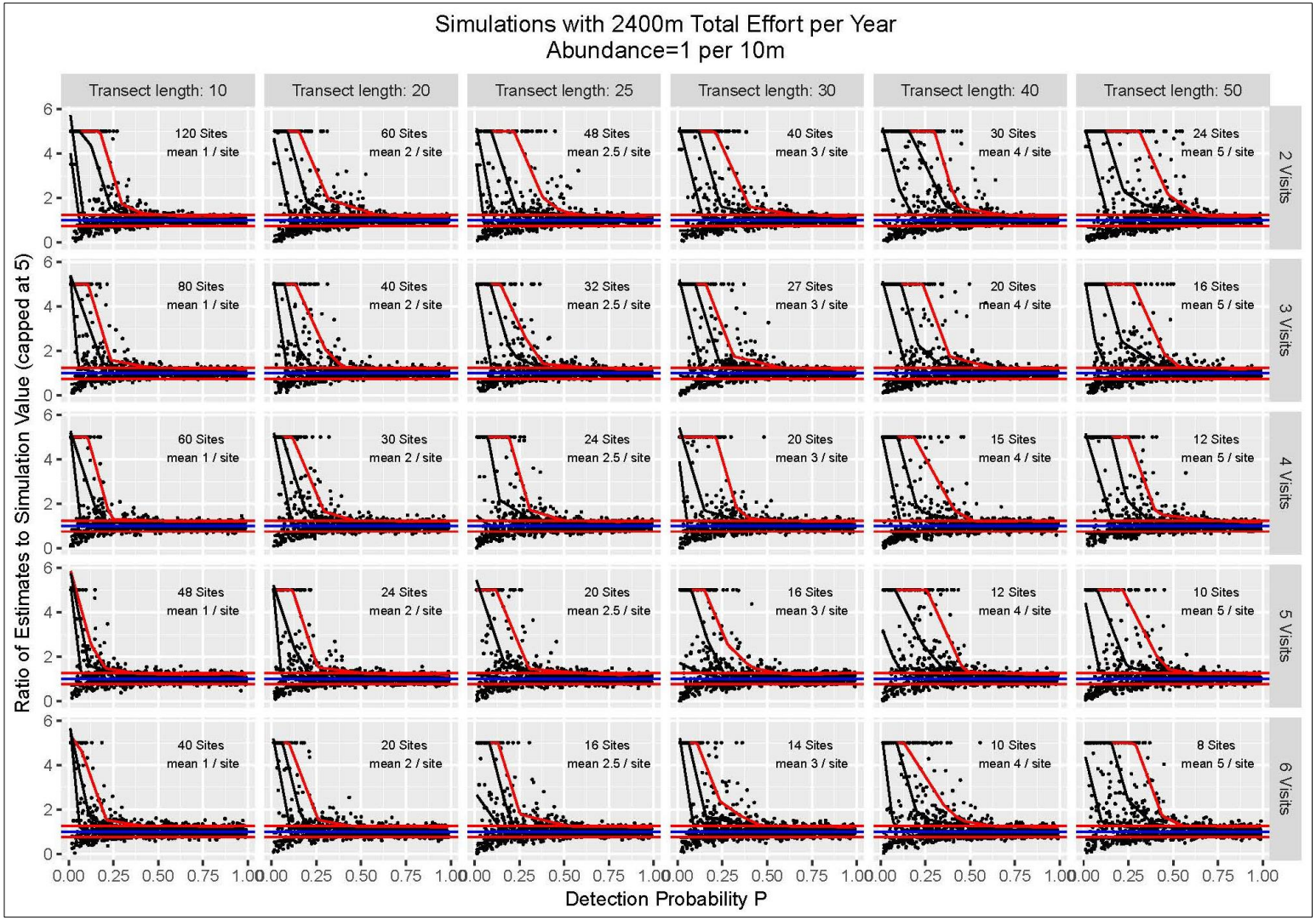


Figure A3-8. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 1 per 10 meters (32.8 ft).

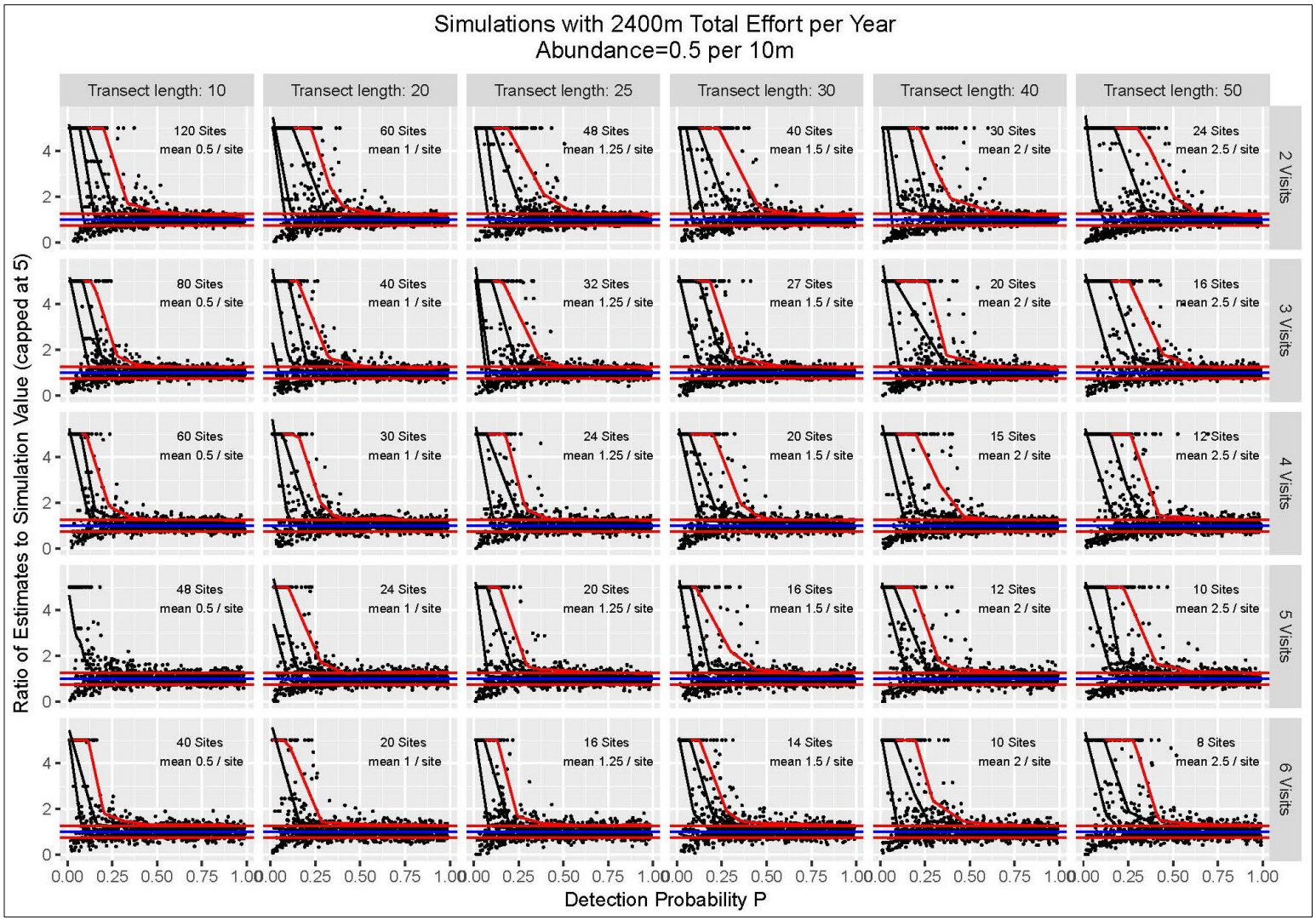


Figure A3-9. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 0.5 per 10 meters (32.8 ft).

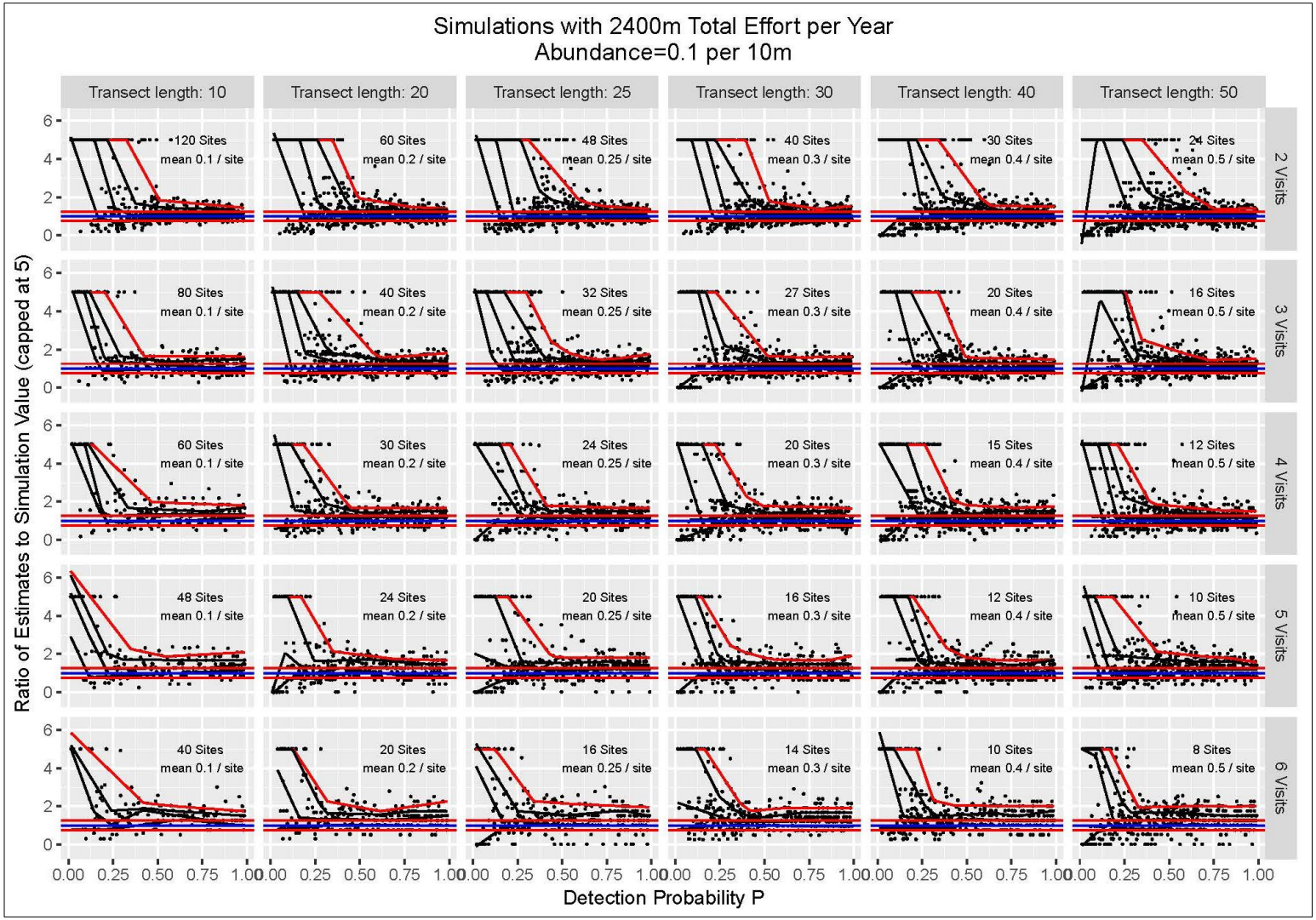


Figure A3-10. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 2,400 meters Total Effort per Year. Abundance equals 0.1 per 10 meters (32.8 ft).

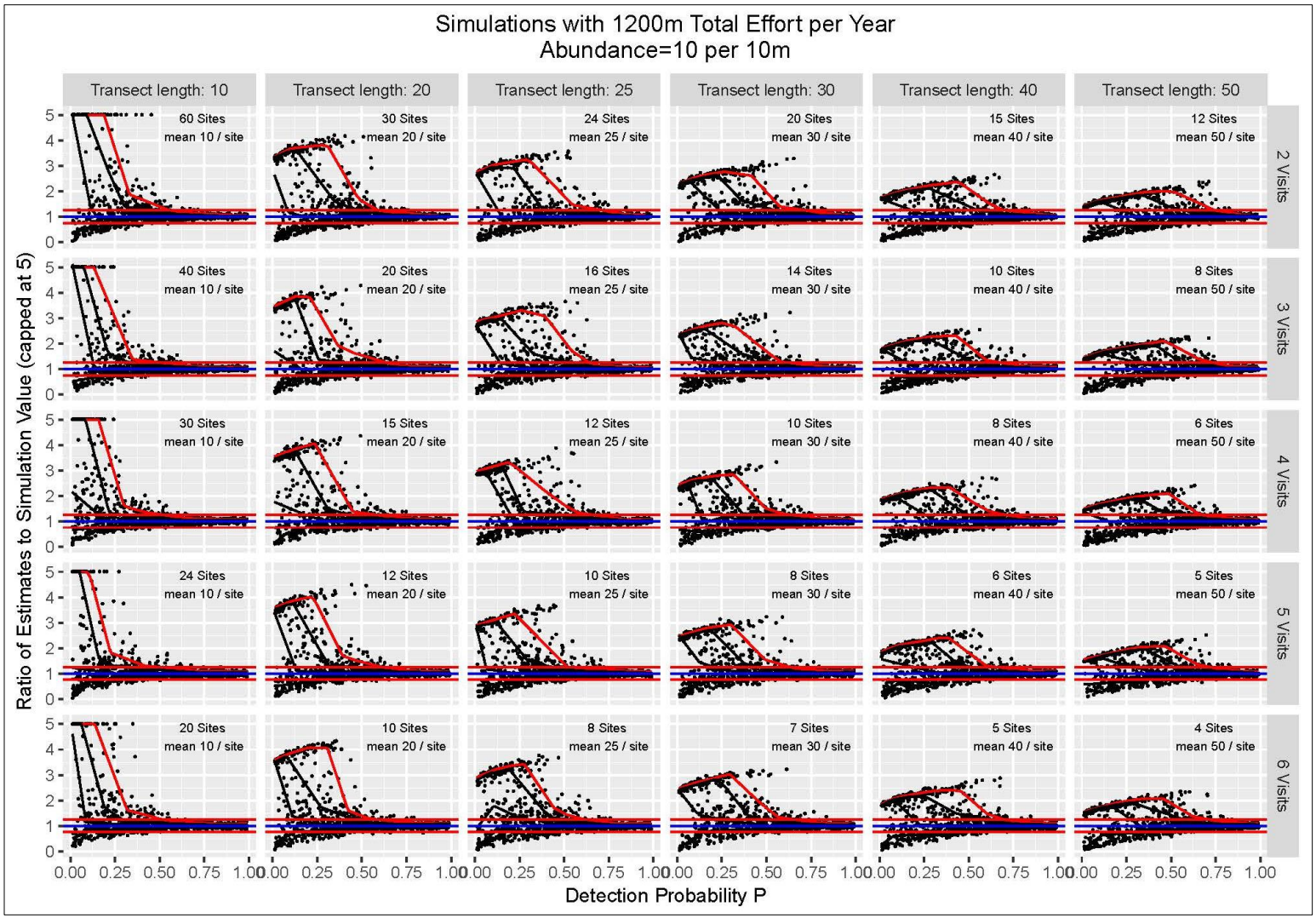


Figure A3-11. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 10 per 10 meters (32.8 ft).

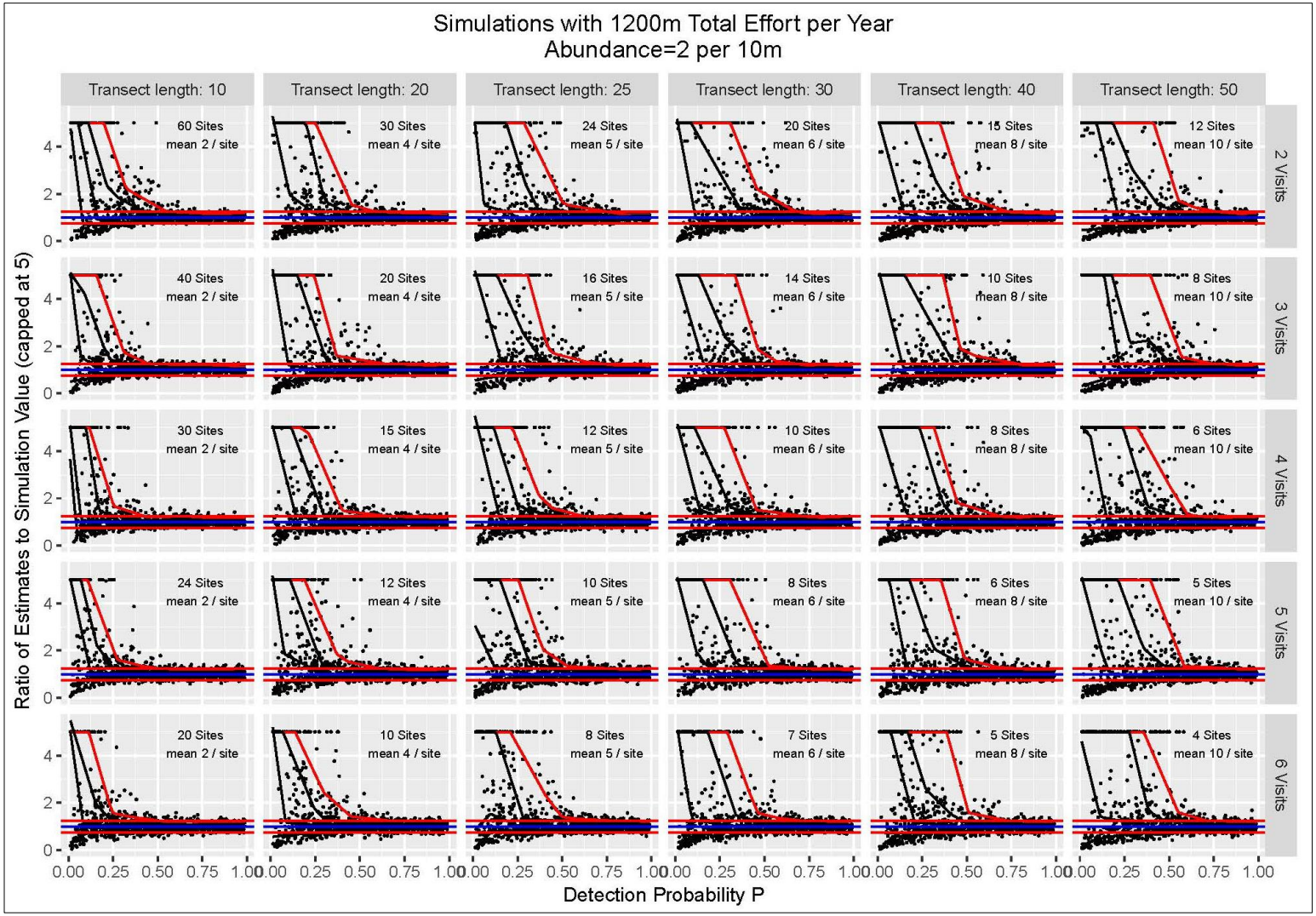


Figure A3-12. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 2 per 10 meters (32.8 ft).

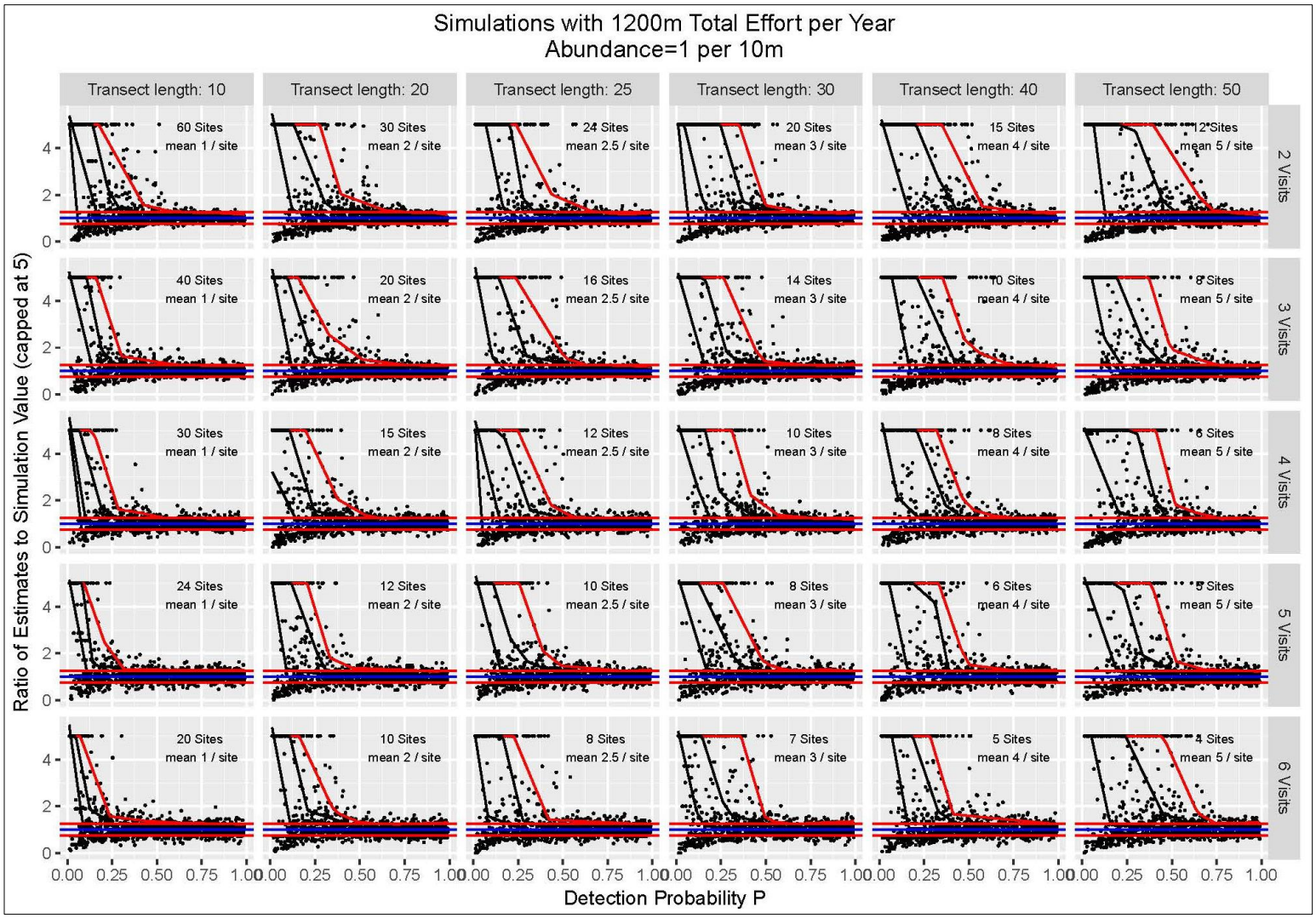


Figure A3-13. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 1 per 10 meters (32.8 ft).

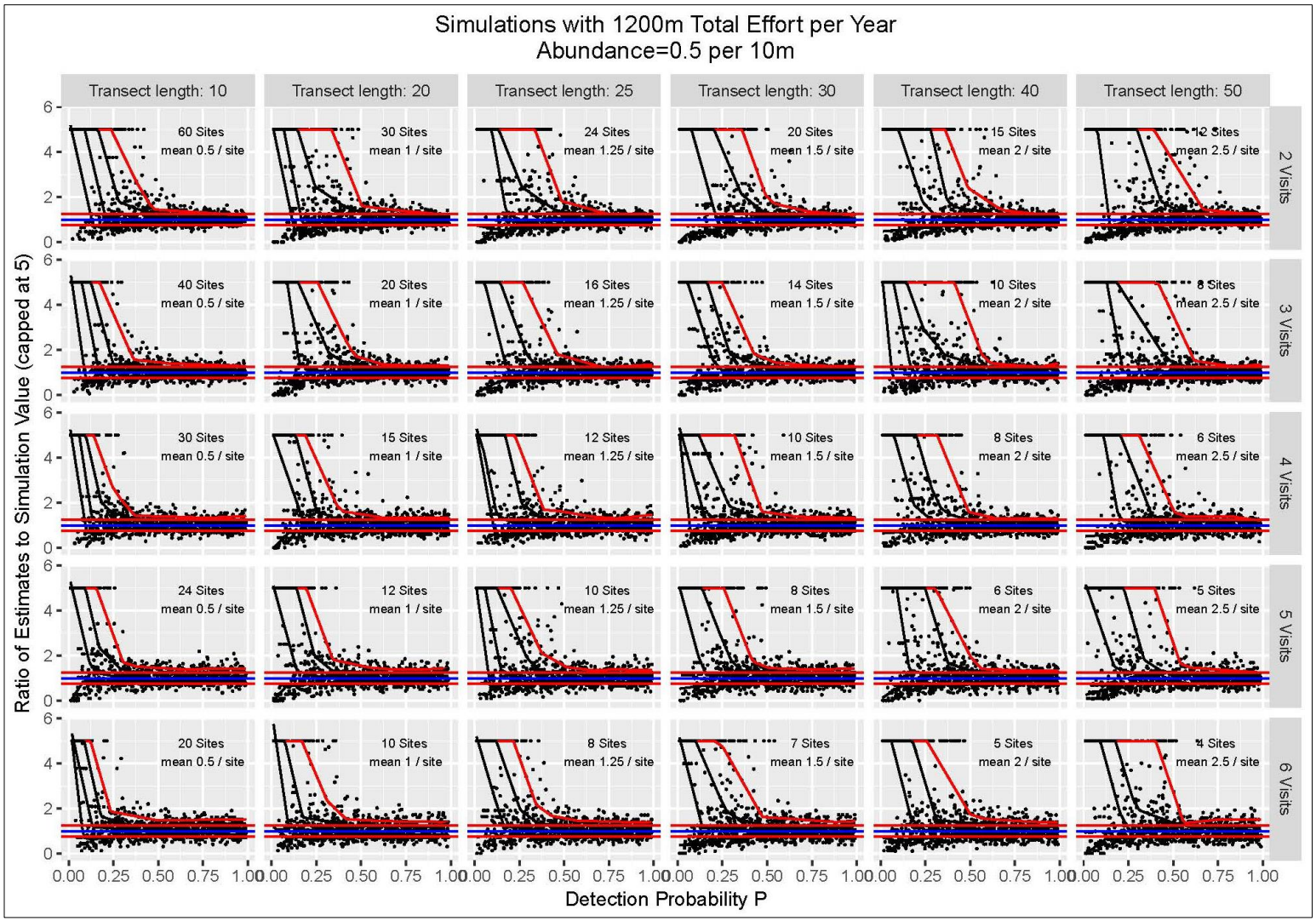


Figure A3-14. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 0.5 per 10 meters (32.8 ft).

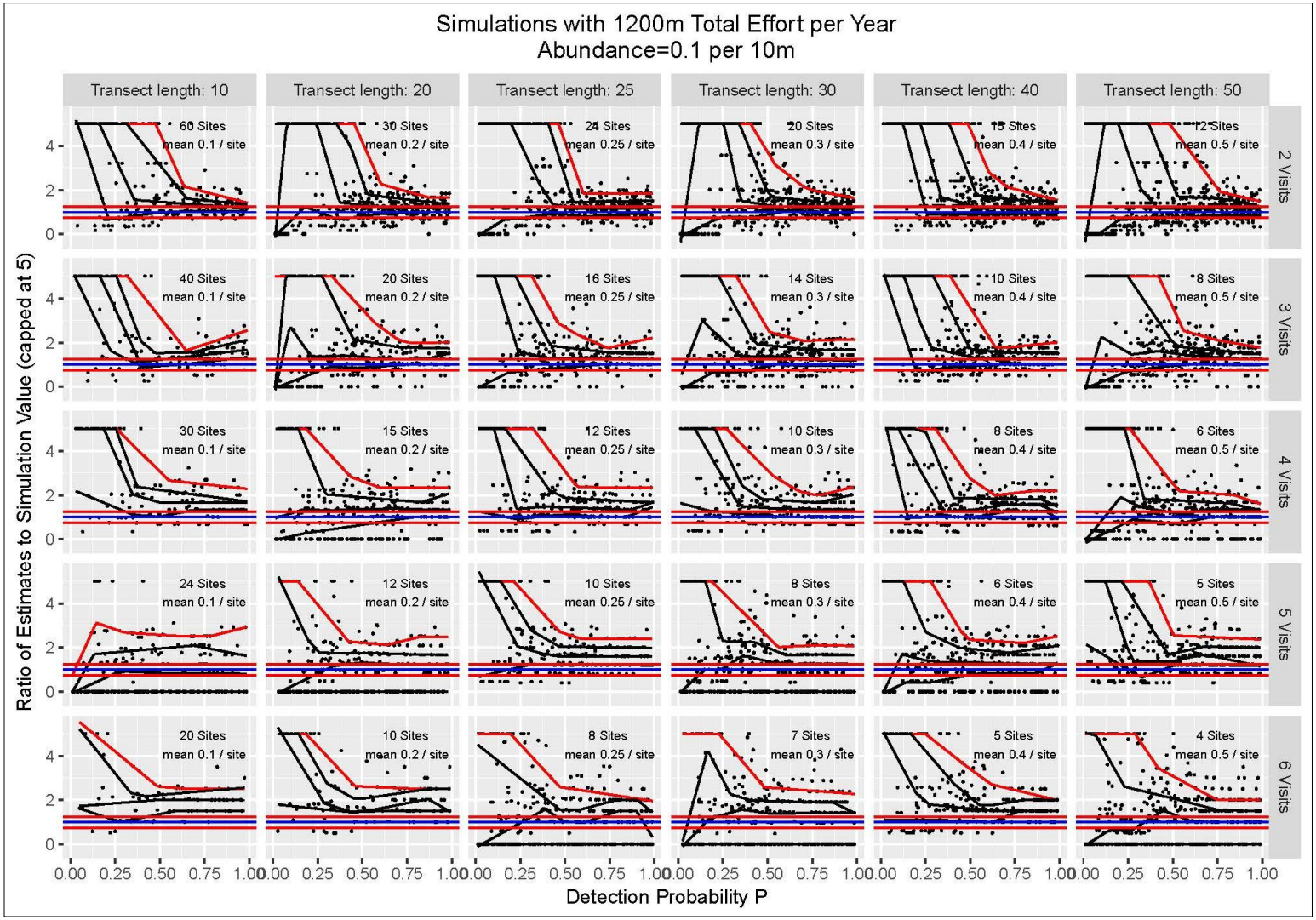


Figure A3-15. Estimated abundance per transect as a function of individual detection probability p, for combinations of total effort (4,800; 2,400; and 1,200 meters [15,748; 7,874; and 3,937 ft]), mean abundances (noted as mean per 10 meters [32.8 ft]), transect lengths (10, 20, 25, 30, 40, 50 meters [32.8, 65.6, 82.0, 98.4, 131.2 and 164.0 ft]), and numbers of visits per year (2, 3, 4, 5, or 6). X axis is detection probability. Values on the Y axis greater than 5 are truncated to 5. The horizontal blue and red lines are the true and +/- 25% values as in Figure 2. The curved red line is the 90th percentile of the estimates for that value of the detection probability. The 3 curved black lines are the 25th, 50th, and 75th percentiles of the estimates for that value of the detection probability. Above graph shows Simulations with 1,200 meters Total Effort per Year. Abundance equals 0.1 per 10 meters (32.8 ft).

Within a column of transect lengths, increasing the number of visits from two to three usually lowered the minimum detection probability required for reliable estimates, but more than three visits essentially broke even between the increased visits and decreased number of sites. As abundances decrease, the tradeoff becomes clearer: more sites and fewer revisits produces more accurate estimates at high detection probabilities but a larger minimum detection probability required to avoid very bad estimates (e.g., the left column of page 26: effort=4800 abundance=0.5/10meters [32.8 ft]). However, increasing to five or six visits per site did very little to decrease the minimum detection probability required for reliable estimates.

The general result of these simulations is that even for inferences to the entire cave (all 4,800 meters [15,748 ft] of effort combined), and at the maximum abundance of 1 per meter (3.3 ft), reliable estimates are produced only for detection probabilities greater than 0.3–0.4. At lower detection probabilities, not only does the noise or variation of the estimates about the true value increase, the hierarchical model also produces spurious estimates up to six times the true value. The magnitude of these misleading estimates is greatest for short transects, but the maximum detection probability with spurious estimates increases with increasing transect length. These problems increase in magnitude and prevalence for lower abundances.

Note for comparison that Figure 6.6 in Kéry and Royle (2015) explores this same model, but for mean abundances of five per site, from 20 to 250 sites, and 2, 5, or 10 revisits to each site. It, too, has spurious gross overestimates (greater than 60x) for a fraction of the simulations with low detection probabilities. Unlike these simulations, that figure does not hold the total effort constant. Rather, it demonstrates how to determine the required effort in terms of sample size and number of revisits, with more sites and more visits providing reliable estimates for lower detection probabilities. These simulations do hold the effort constant, and explore parameter combinations toward the upper left of Figure 6.6 and beyond (Kéry and Royle 2015). In general, the magnitude of the spurious overestimation is greatest for short transect lengths, but the maximum detection probability at which it still occurs increases with transect length. One can reduce the probability of a spurious overestimate, but at the cost of even greater magnitude of the overestimate. Without independent evidence for the population size, there will be no way to determine whether an estimate in spurious.

The other major potential failure of this approach is for the hierarchical model to fail to converge on any parameter estimates at all. While this is not as dangerous for park resource management as spurious overestimates, it still represents a failure of the sampling to yield information about the population sizes. The fractions of simulations where the models failed to produce any estimate of abundance are shown in Figure A4-1 through A4-3. While the blue dots for spurious estimates increase at higher abundances when dividing the 4,800 meters (15,748 ft) effort into two or four separate basins, the fraction of simulations producing no estimates remains nearly 0 for higher abundances even when dividing the effort.

This is primarily a problem for low abundances of 0.1 per 10 meters (32.8 ft), where the expected total number of individuals in transects is only 8–24 (48 divided by the number of revisits). Fewer revisits and longer transects minimize this problem, more revisits and shorter transects can make up to 75% of the simulations fail to produce estimates. Logistic regressions were used to determine if low detection probabilities contribute to this issue. The fraction of failures was fit as a function of the detection probability p for each combination of the other parameters. There tended to be a slight effect of

probability of failure decreasing with increasing detection probability, but that effect was very weak compared to the differences across transect lengths and revisits, and some individual parameter combinations produced slight (non-significant) decreases in failure probability with increasing detection probability.

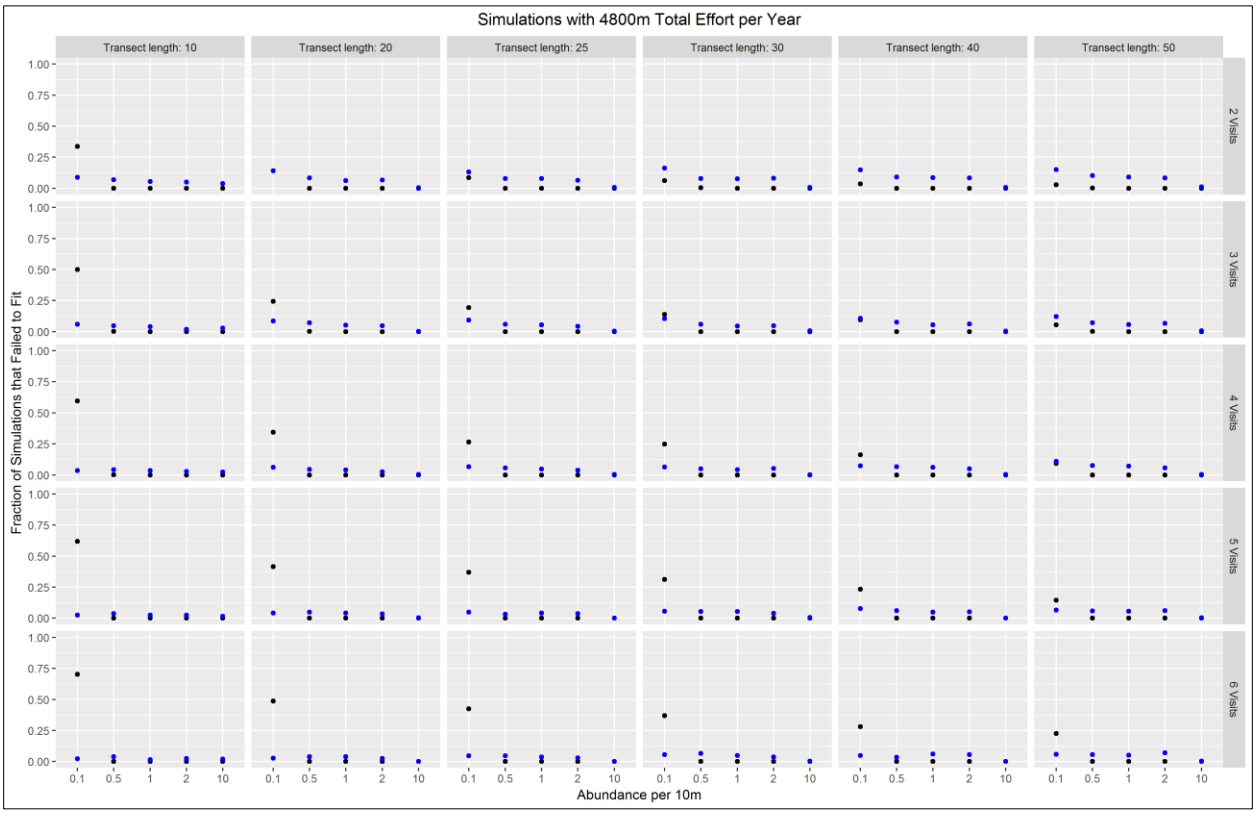


Figure A4-1. Fractions of simulations failing to generate estimates (black dots) and where the abundance estimate is greater than five times the true value (blue dots). Above graph shows Simulations with 4,800 meters (15,748 ft) Total Effort per Year.

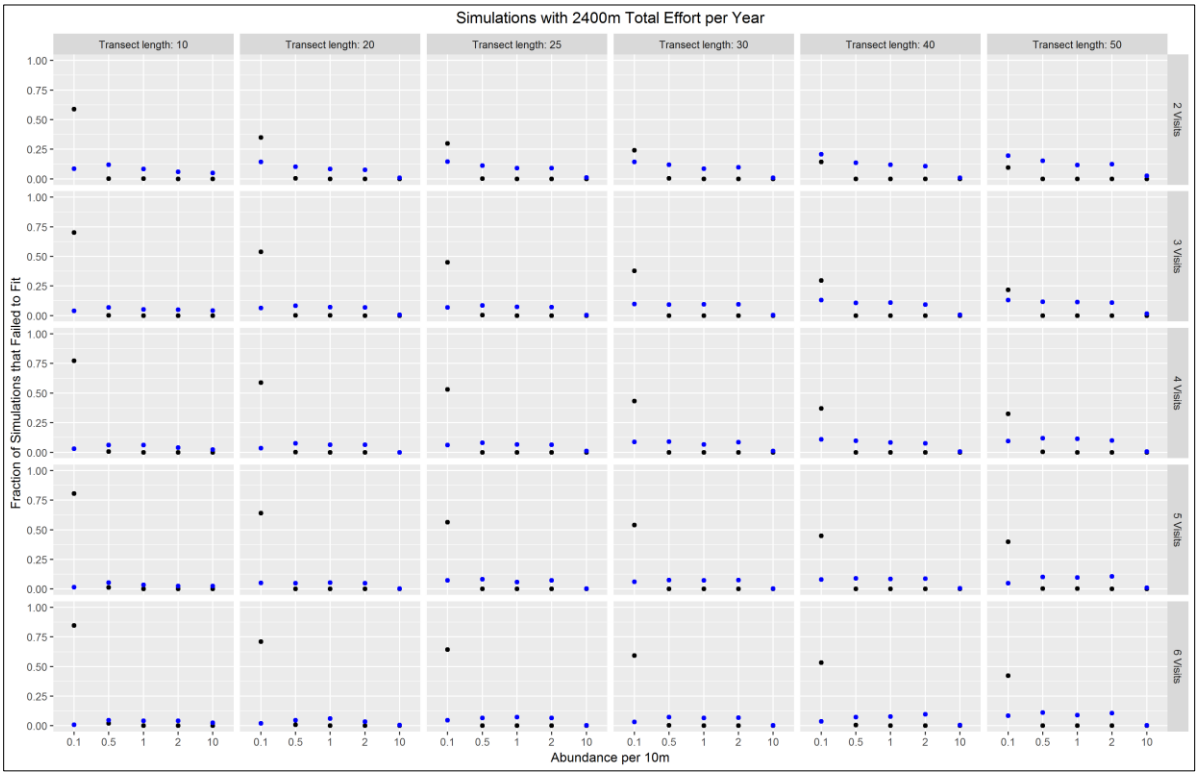


Figure A4-2. Fractions of simulations failing to generate estimates (black dots) and where the abundance estimate is greater than five times the true value (blue dots). Above graph shows Simulations with 2,400 meters (7,874 ft) Total Effort per Year.

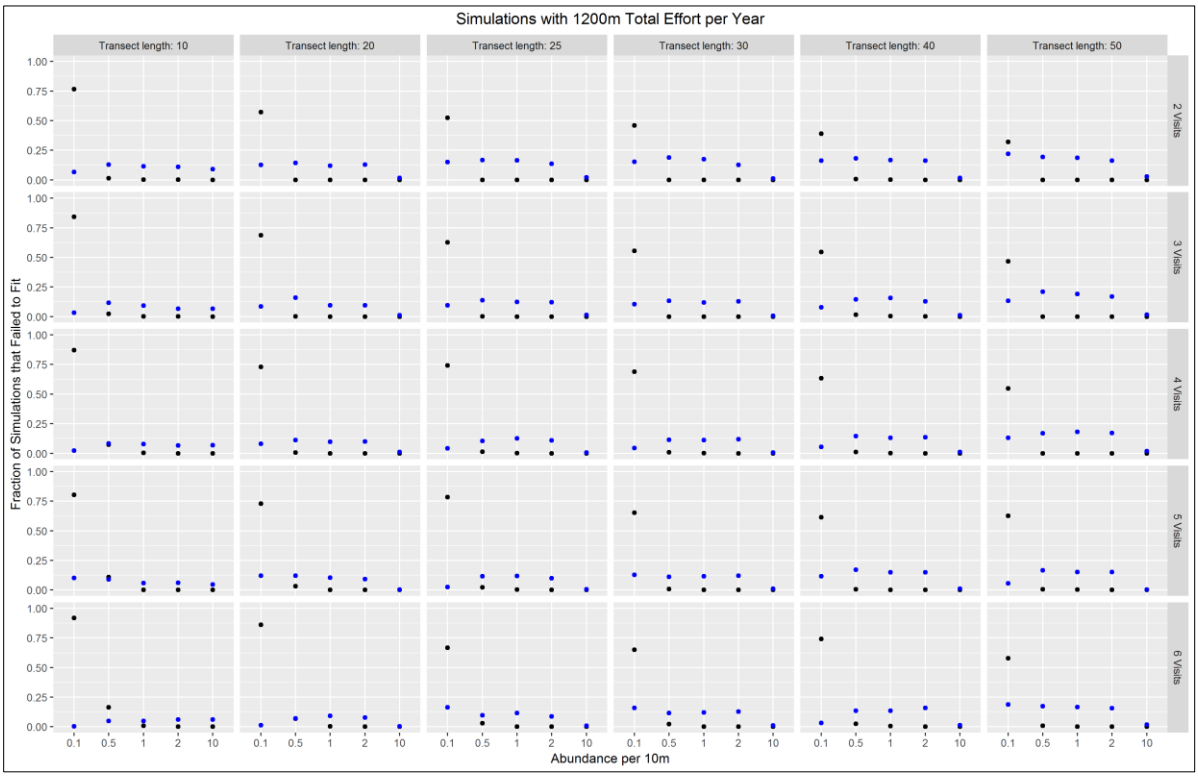


Figure A4-3. Fractions of simulations failing to generate estimates (black dots) and where the abundance estimate is greater than five times the true value (blue dots). Above graph shows Simulations with 1,200 meters (3,937 ft) Total Effort per Year.

Discussion

The take home message of these simulations is that for the plausible ranges of abundances and detection probabilities and the specified sampling effort, hierarchical models are likely to provide useful estimates for only the most abundant one or two species. For the other species, this approach has substantial risks of obtaining data that models simply cannot derive estimates from. And, even more of a problem, there is a substantial risk of this approach producing spurious estimates of abundance five or more times the true values.

Chris Sutherland's estimates from the Bridge Ave pilot data give some indication of the risk, as three of his four estimates of detection probabilities are in the 0.3–0.4 range. *Caecidotea stygia* (CAST) has a high detectability of 0.73 (with low standard error) and densities of 0.2–0.3 per meter (3.3 ft). For large numbers of shorter transects, non-spurious estimates of CAST abundances should be possible even at 1,200 meters (3,937 ft) effort (four basins). *Orconectes pellucidus'* (ORPE) abundances of 0.95 per meter (3.3 ft) are high enough that the estimated detection probability of 0.3 makes spurious overestimates unlikely for park-wide estimates and larger numbers of shorter transects. However, there is a greater than 10% chance of spurious estimates at the four-basin scale (1,200 meters [3,937 ft] effort each). Also, the standard error of the estimated detection probability is 0.09; even 1 standard error below the estimate has greater than 10% of the simulations producing abundance estimates more than twice the true value at the park-wide level. *Typhlichthys subterraneus* (TYSU) and *Stygobromus vitreus* (STVI) are at lower abundances, but also borderline detectabilities for park-wide estimates, and at risk of spurious results for two- or four-basin estimates. If the true detection probabilities are even slightly lower than the estimates, there is a substantial risk of spurious abundance estimates for these species at the park-wide scale. Finally, note that *Cambarus tenebrosus* (CATE) and *Copepod* (COPE) models did not converge and produce estimates for Chris Sutherland. The Bridge Avenue pilot data, with twenty 20-meter (65.6-ft) transects and two visits, included only one CATE and two COPE. Even with six times the effort, those species are unlikely to produce reliable results for estimated abundance.

Estimation of Temporal Trends

Despite the above issues with estimating single-year abundance, estimation of temporal trends must also be explored. Estimation of trends has the advantage of accumulating multiple years of data. If the trend is constrained to be linear, monotonic, or a low-degree polynomial, a single year of data that may give spurious abundance estimates or no estimates leverages preceding and succeeding years to provide valid estimates of both status and trend.

Simulations of temporal trends require much more complex data, and different change processes (e.g., birth-death versus immigration-emigration) produce different patterns in the simulated data for a given mean trend. I simulated a super-population undergoing the trend homogeneously across space, with sites as samples from each year's overall population density. Other formulations are reasonable and might be more relevant.

For each simulation, a set of population mean densities per transect (lambdas) were generated from the initial density (abundance per m times transect length), a multiplicative decline of 0.95 or 0.9 for each subsequent year (5% or 10% decline per year), for a total of 15 years. From this set of annual population abundances, an additional year to year fluctuation component was added by multiplying each annual lambda by a normal deviate with mean 1 and sd 0.1. This year to year fluctuation reflects year to year variation in precipitation or other factors that affect abundances in the sampleable streams, but are not persistent deviations impacting subsequent years. Most Inventory and Monitoring Division (IMD) protocols omit year to year fluctuations from their power analyses, and thus grossly overestimate the power to detect trends. The magnitude of sd=0.1 is the lower end of the range of I've estimated from terrestrial monitoring results. Pilot data and ecological knowledge may provide a better value for the amplitude of year to year fluctuations for cave aquatic biota.

Then, for each site in that simulation, a true abundance was drawn as a Poisson deviate with that year-specific lambda, and a simulation-specific detection probability was used to drive the binomial detection process to compute how many individuals were observed. In order to estimate power and coverage for trend estimation, detection probabilities p were not randomly across a range of values. Instead, 500 simulations were run for each of five specific values of p: 0.2, 0.4, 0.6, 0.8, and 0.9.

```
# Data generation

# for each site, covariate of Year <- 0:(nYears-1), lambda as
Poisson mean for that year

Year <- rep(0:(nYears-1), times=Txx$nSite[Tsim])

Lambdas <- (Txx$abund[Tsim] * Txx$tlength[Tsim]) *
Txx$decline[Tsim]^(0:(nYears-1))

# Now (multiplicative) year to year variation with sd=0.05

Lambdas2 <- Lambdas * rnorm(nYears,1,sd=Y2Ysd)
```

```
N <-
rpois(Txx$nSite[Tsim]*nYears,rep(Lambdas2,times=Txx$nSite[Tsim])
)

# actual numbers

Obs <- matrix(data=rbinom(length(N)*Txx$nVisit[Tsim],


size=rep(N,each=Txx$nVisit[Tsim]),

                                                prob=detects[pp]),

                          ncol=Txx$nVisit[Tsim], byrow=TRUE)
```

From that block of data for a set of sites, the n-mixture model for trend was fit to 5, 6, 8, 10, 12, and 15 years, with Year as a continuous covariate for constant multiplicative change per year.

```
for (mY in 1:length(monYears)) {         # currently 6

     # Bundle data for unmarked

    umf <- unmarkedFramePCount(y = Obs[Year<=monYears[mY],],


siteCovs=data.frame(Year=Year[Year<=monYears[mY]])))

    fm <- try(pcount(~1~Year,umf)))  # currently called 30x per
sim

} # bottom loop over mY
```

Note that both sets of simulations require substantial numbers of cpu hours. The actual code included as appendices uses *doParallel* and *foreach* to run on multiple cores and thread servers (and some artefacts of separate hunks run on different computers).

Results and Discussion

As expected, with multiple years of data, nearly all simulations produced estimates of trends. Only eight out of the 2,460,000 tests failed to provide estimates. All eight failures had total effort of 1,200 meters (3,937 ft), transect lengths of 10 meter (32.8 ft), four visits, 30 sites, abundances of 0.1 per 10 meters (32.8 ft), and detection probabilities of 0.2; two had declines of 0.95 and six had declines of 0.95. More to the point, these were all short monitoring durations for those parameters. Of the six failures at five-year durations, four fit estimates once the sixth year of data was added. The other two simulations failed to fit with both five and six years, but fit estimates with eight years and above.

Conventional power analyses to detect a decline at $\alpha=0.05$ are shown in Figures A5-1 to A5-12. Across all combinations of other parameters, two visits per year has more power to detect trends than four visits per year with half as many transects. The power to detect a decline is reasonably strong for the higher abundances, but drops off for lower abundances. This makes sense; at low abundances the binomial variation of finding individuals in transects dominates the decline in the mean abundance. The power to detect a temporal trend increases with monitoring duration: not only do more data accumulate, the cumulative change increases as well.

At the full sampling effort (4,800 meters [15,748 ft] per year), there is greater than 80% power to detect a 50% decline (at 5% or 10% per year) when initial abundance exceeds 0.5 per 10 meters (32.8 ft). Increasing the number of visits or transect length (and reducing the number of sites visited) did not substantially affect the power. Reducing the effort to 2,400 meters (7,874 ft) or 1,200 meters (3,937 ft; to simulate a basin-specific analysis) increased the initial abundance needed for achieving 80% power to one to two individuals per 10 meters (32.8 ft). The power to detect a 25% decline was generally low, and only exceeded 0.8 for the full sampling effort (4,800 meters [15,748 ft]) and maximum abundance (two individuals per 10 meters [32.8 ft]).

These results indicate that there is some power to detect park-wide trends for common species, but that rare species (occurring at fewer than 0.5 per 10 meters [32.8 ft]) will not be detected in sufficient quantities to support statistical trend detection. Although the power analysis did not find any benefit to any particular transect length, using longer transects (e.g., 20 meters [65.6 ft]) may help with logistics and reduce movement of individuals across transect boundaries.

Table A-2. Proportion of original population remaining after 5–15 years of 5% and 10% declines per year.

Years	5% Decline per Year	10% Decline per Year
5	0.774	0.590
6	0.735	0.531
8	0.663	0.430
10	0.599	0.349
12	0.540	0.282
15	0.463	0.206

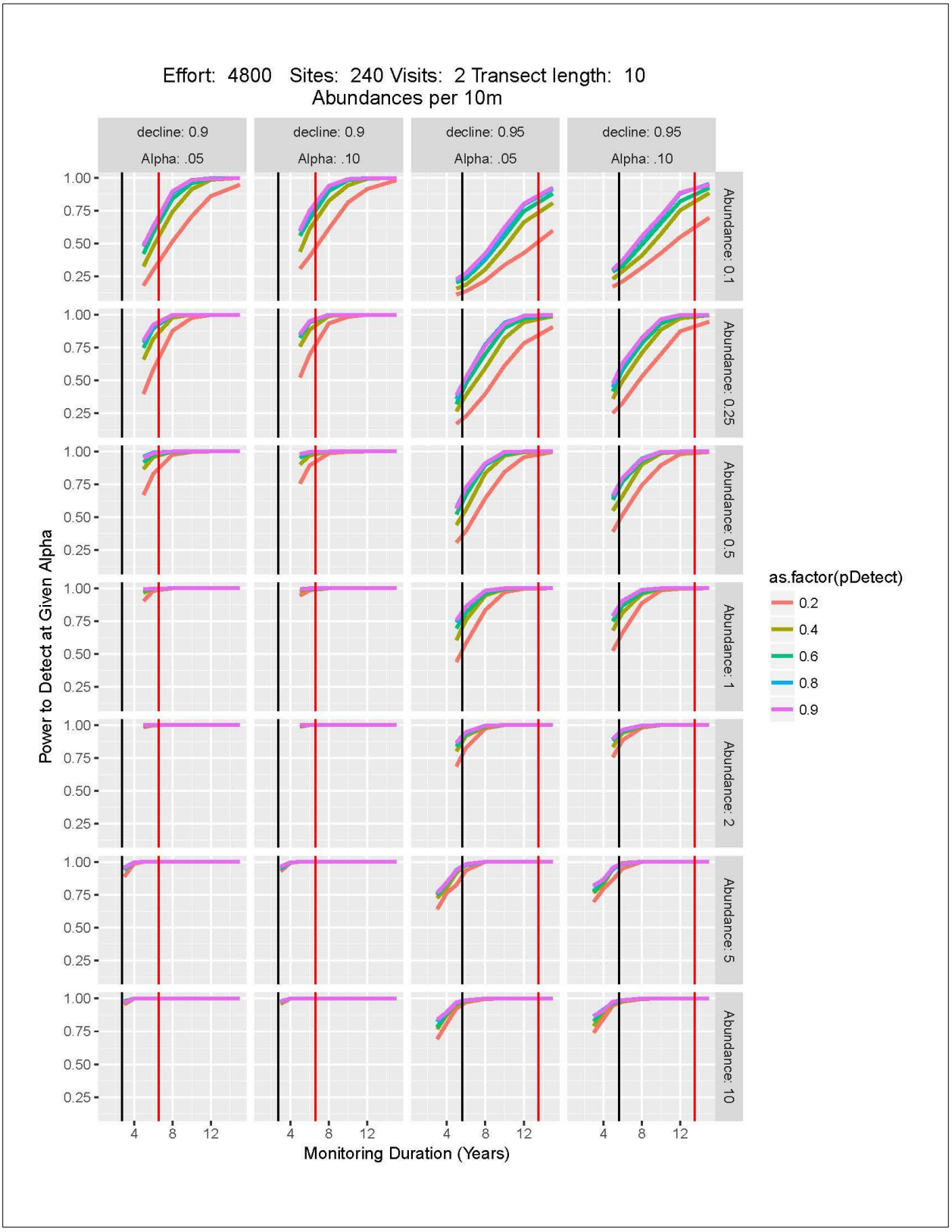


Figure A5-1. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per meter (3.2 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 4800; Sites: 240; Visits: 2; Transect length:10; and Abundances per 10 meters (32.8 ft).

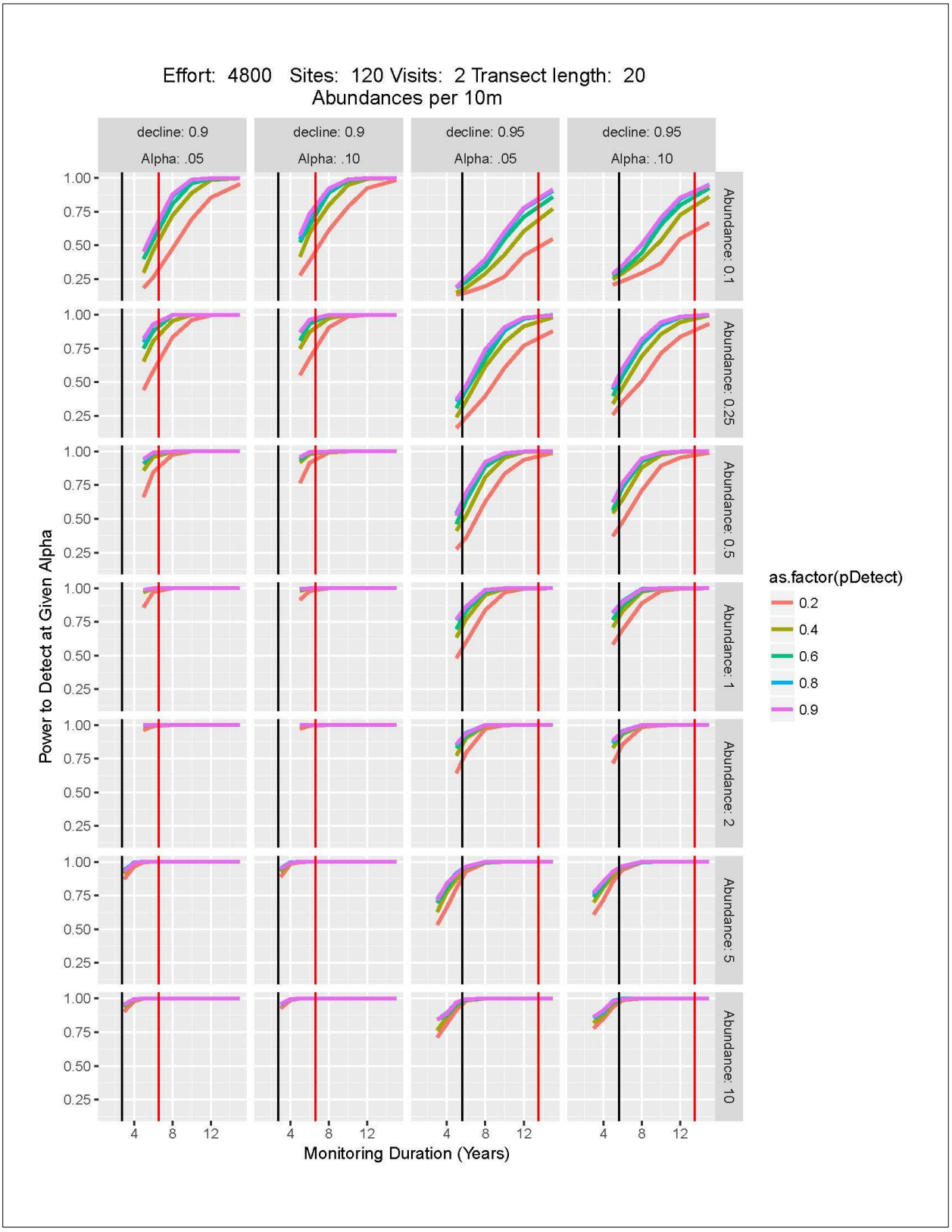


Figure A5-2. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 m (32.8 ft). Above graphs show Effort: 4800; Sites: 120; Visits: 2; Transect length: 20; and Abundances per 10 meters (32.8 ft).

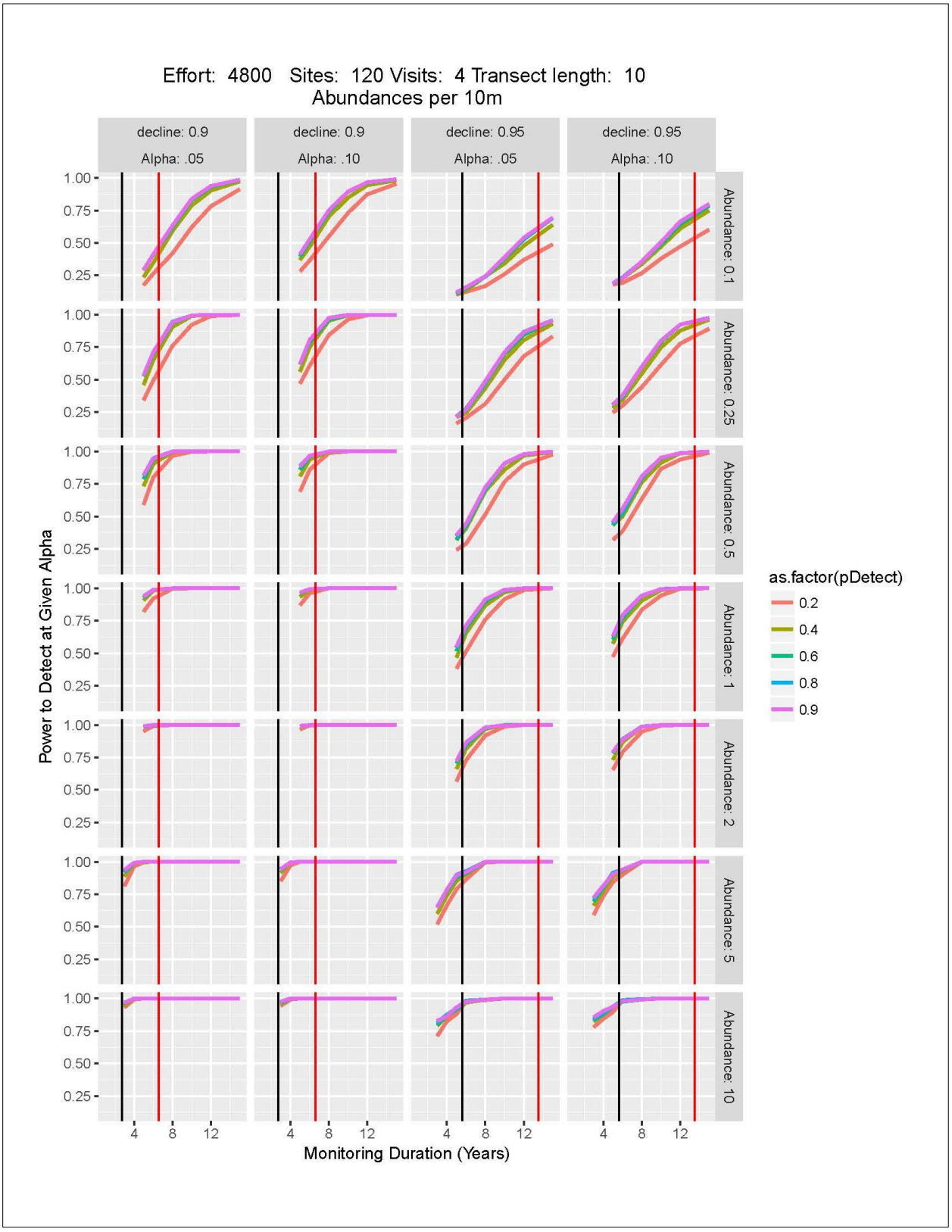


Figure A5-3. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.2 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 4800; Sites: 120; Visits: 4; Transect length: 10; and Abundances per 10 meters (32.8 ft).

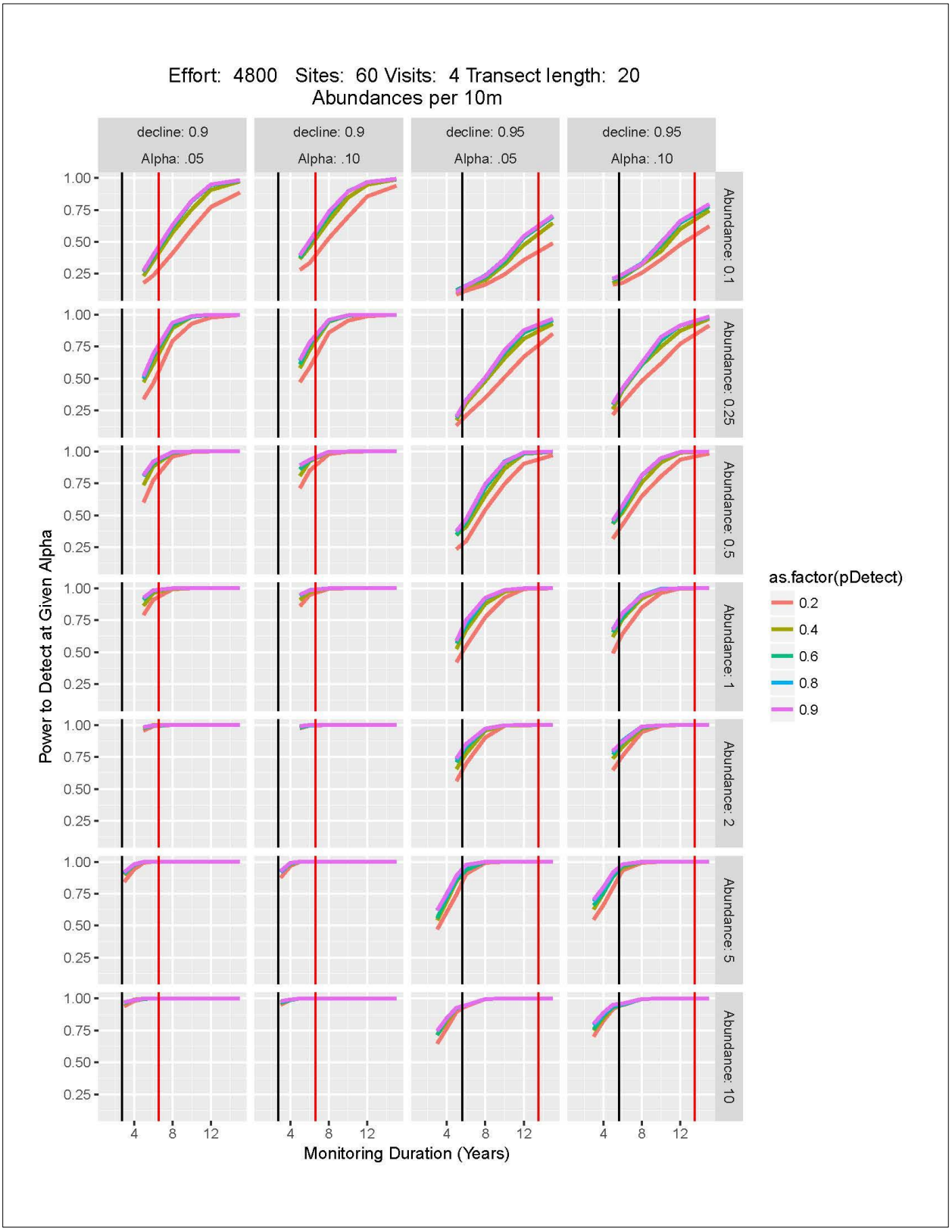


Figure A5-4. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 4800; Sites: 60; Visits: 4; Transect length: 20; and Abundances per 10 meters (32.8 ft).

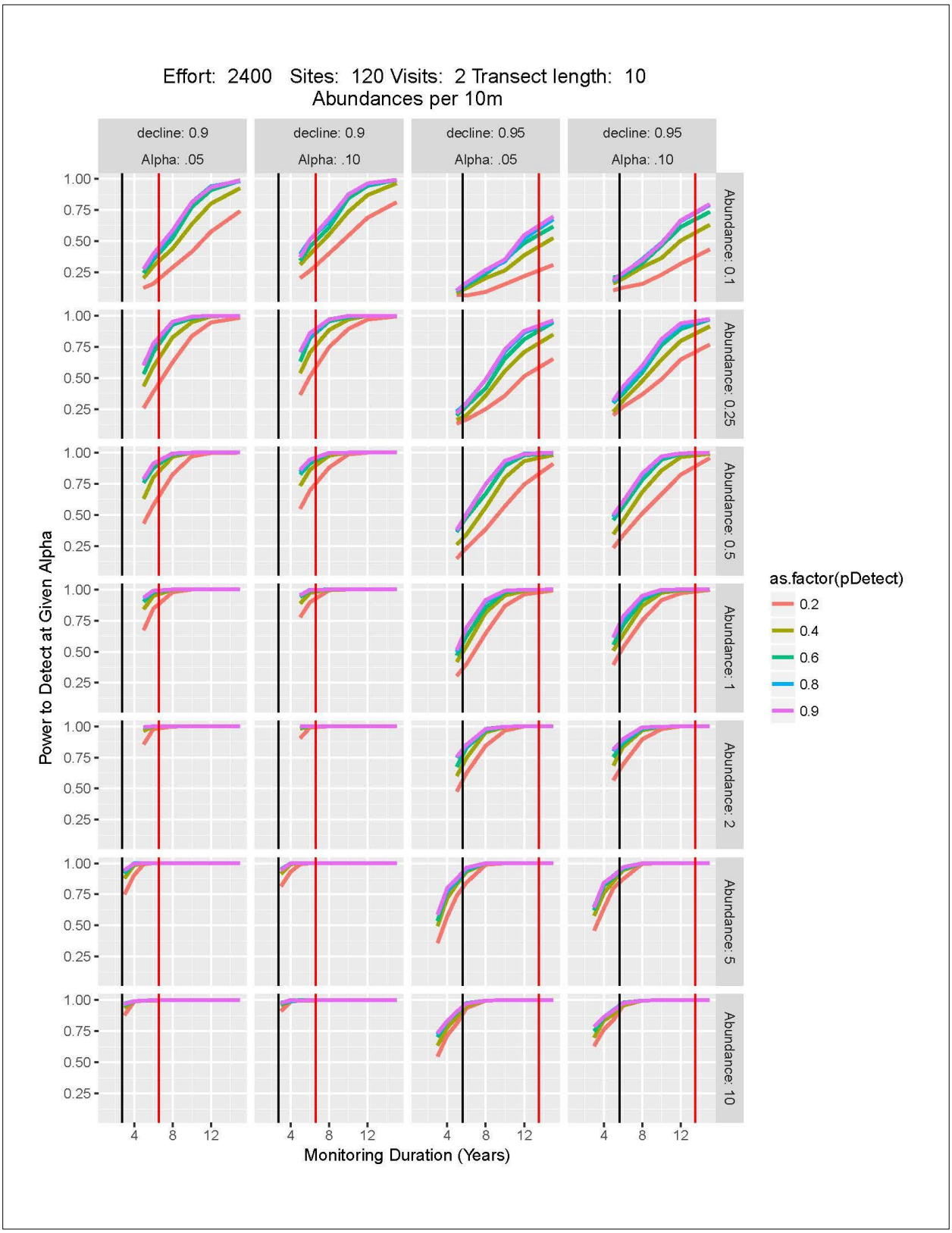


Figure A5-5. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 2400; Sites: 120; Visits: 2; Transect length: 10; and Abundances per 10 meters (32.8 ft).

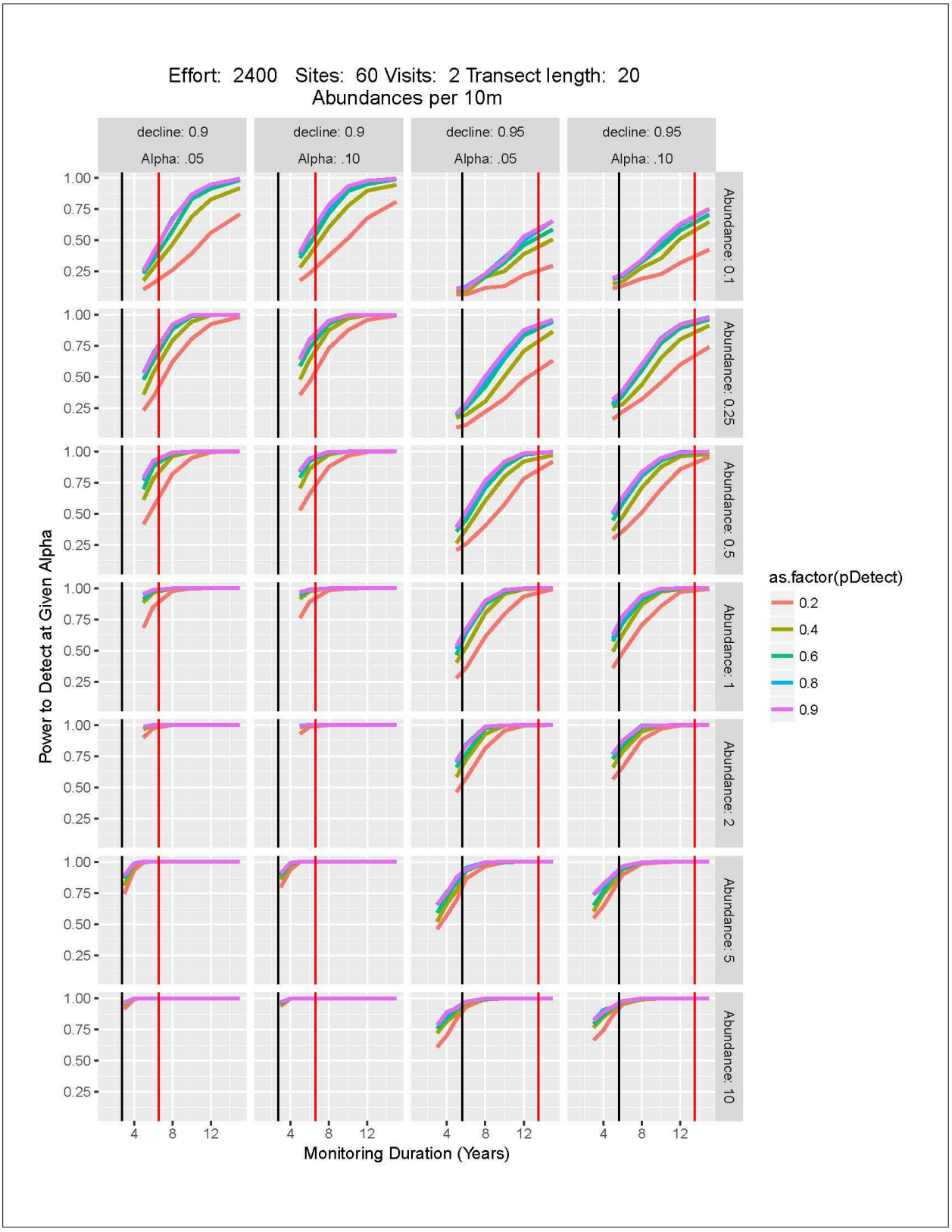


Figure A5-6. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 2400; Sites: 60; Visits: 2; Transect length: 20; and Abundances per 10 meters.

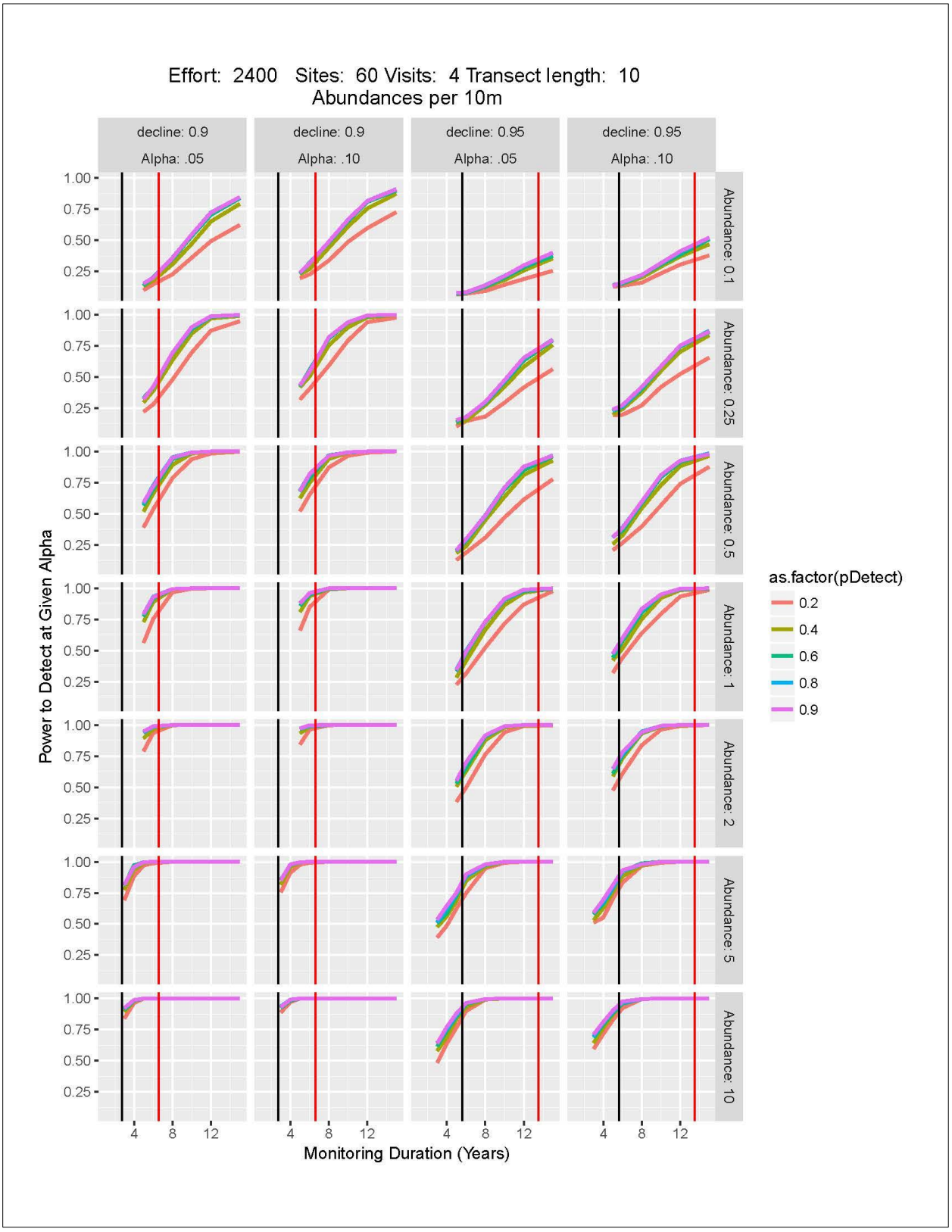


Figure A5-7. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 2400; Sites: 60; Visits: 4; Transect length: 10; and Abundances per 10 meters (32.8 ft).

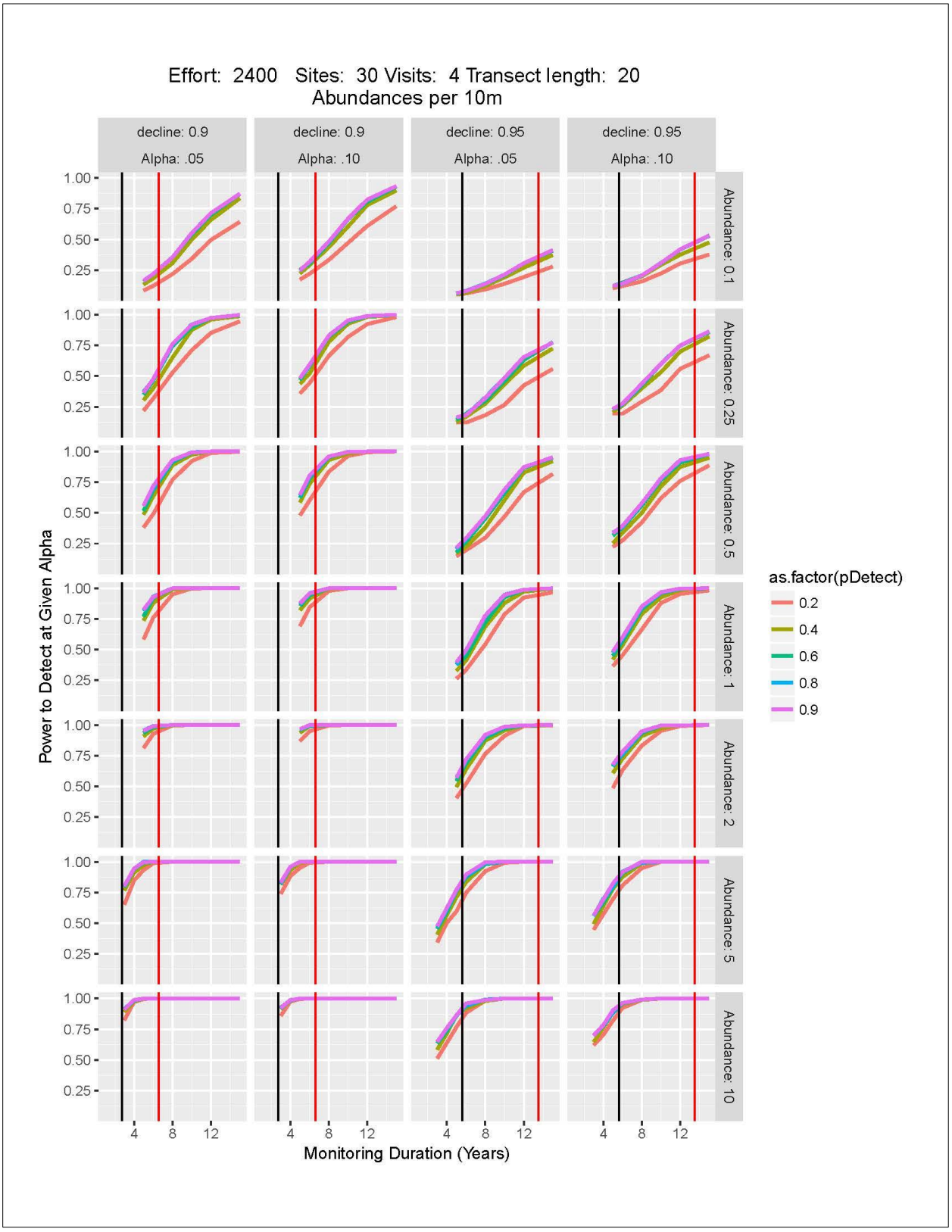


Figure A5-8. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 2400; Sites: 30; Visits: 4; Transect length: 20; and Abundances per 10 meters (32.8 ft).

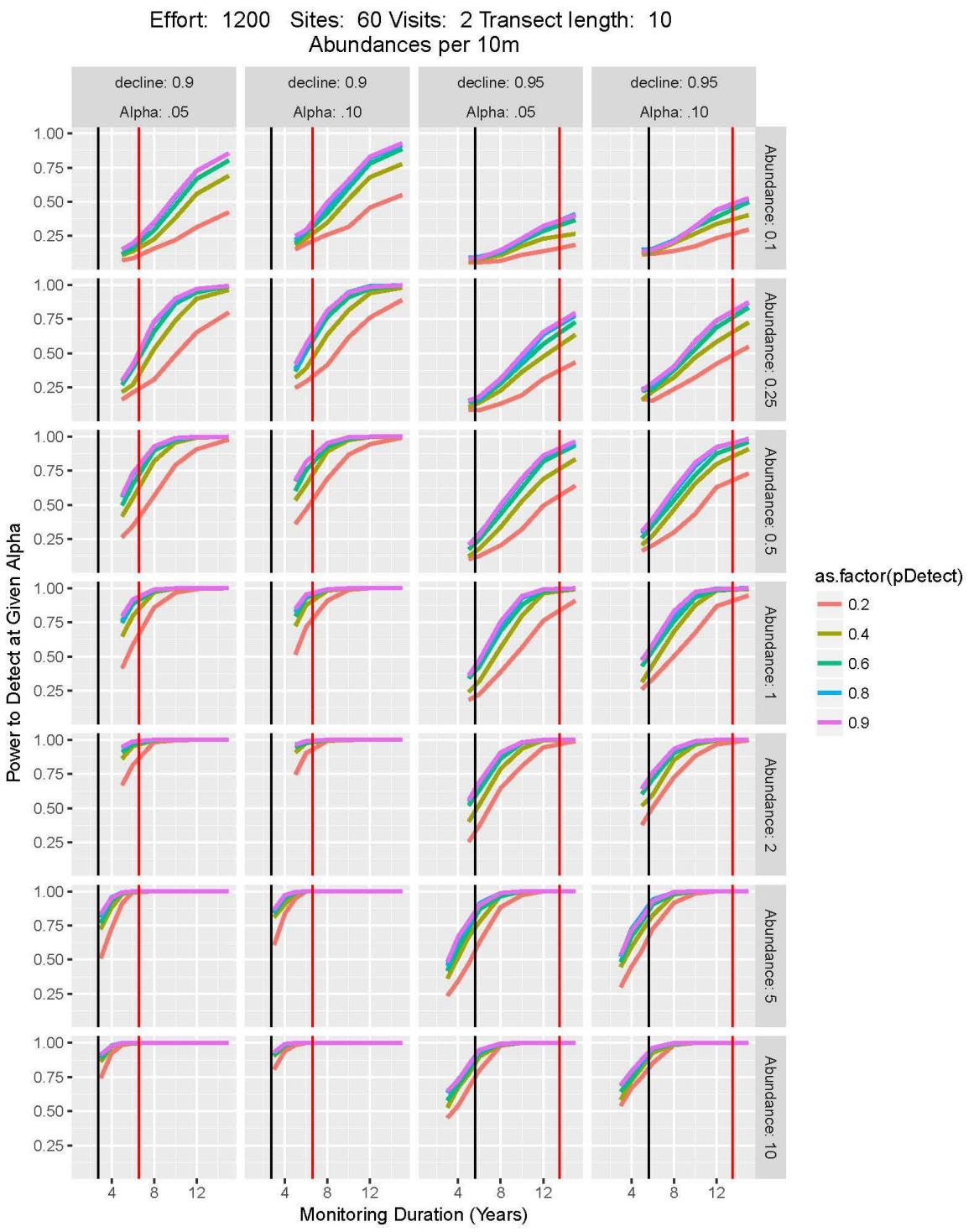


Figure A5-9. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 1200; Sites: 60; Visits: 2; Transect length: 10; and Abundances per 10 meters (32.8 ft).

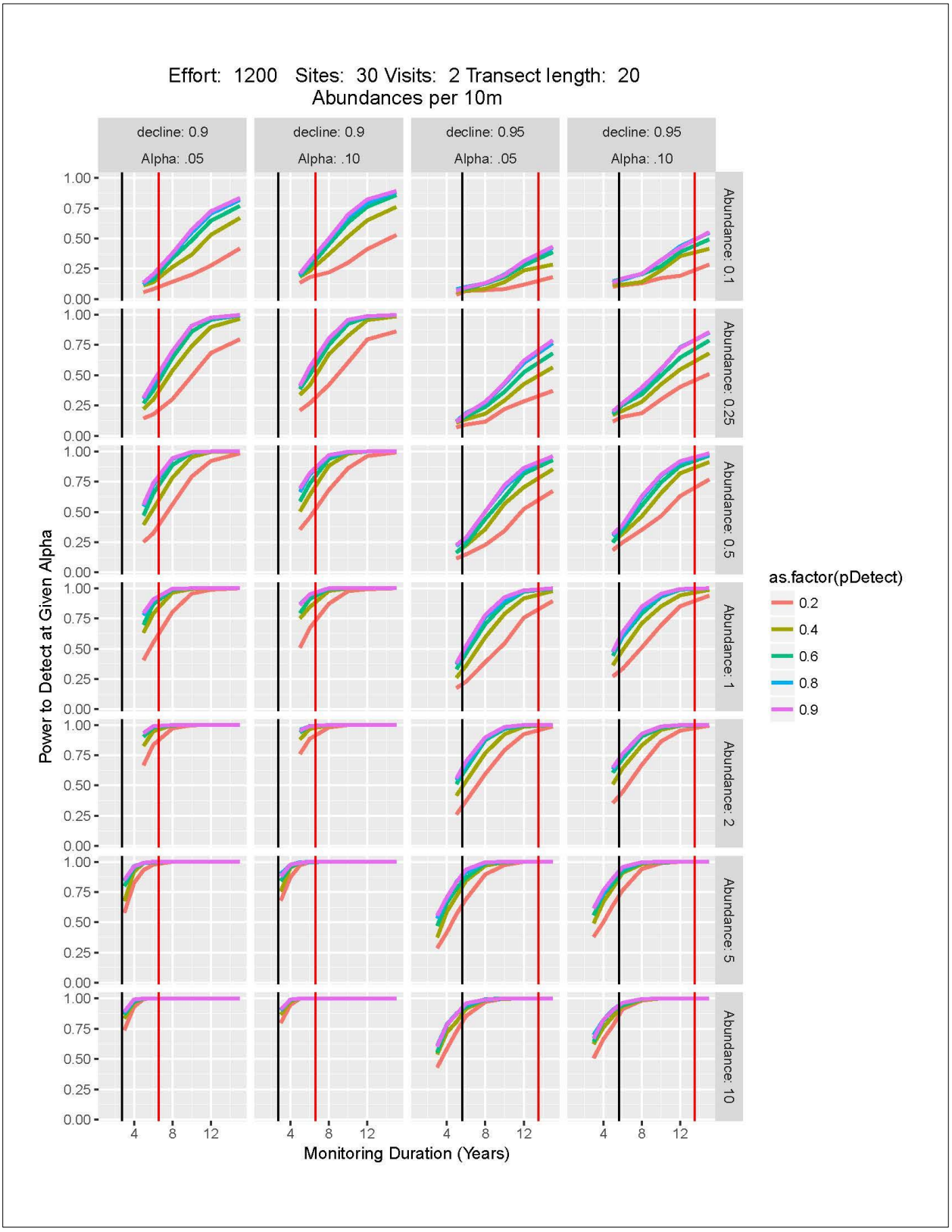


Figure A5-10. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 1200; Sites: 30; Visits: 2; Transect length: 20; and Abundances per 10 meters (32.8 ft).

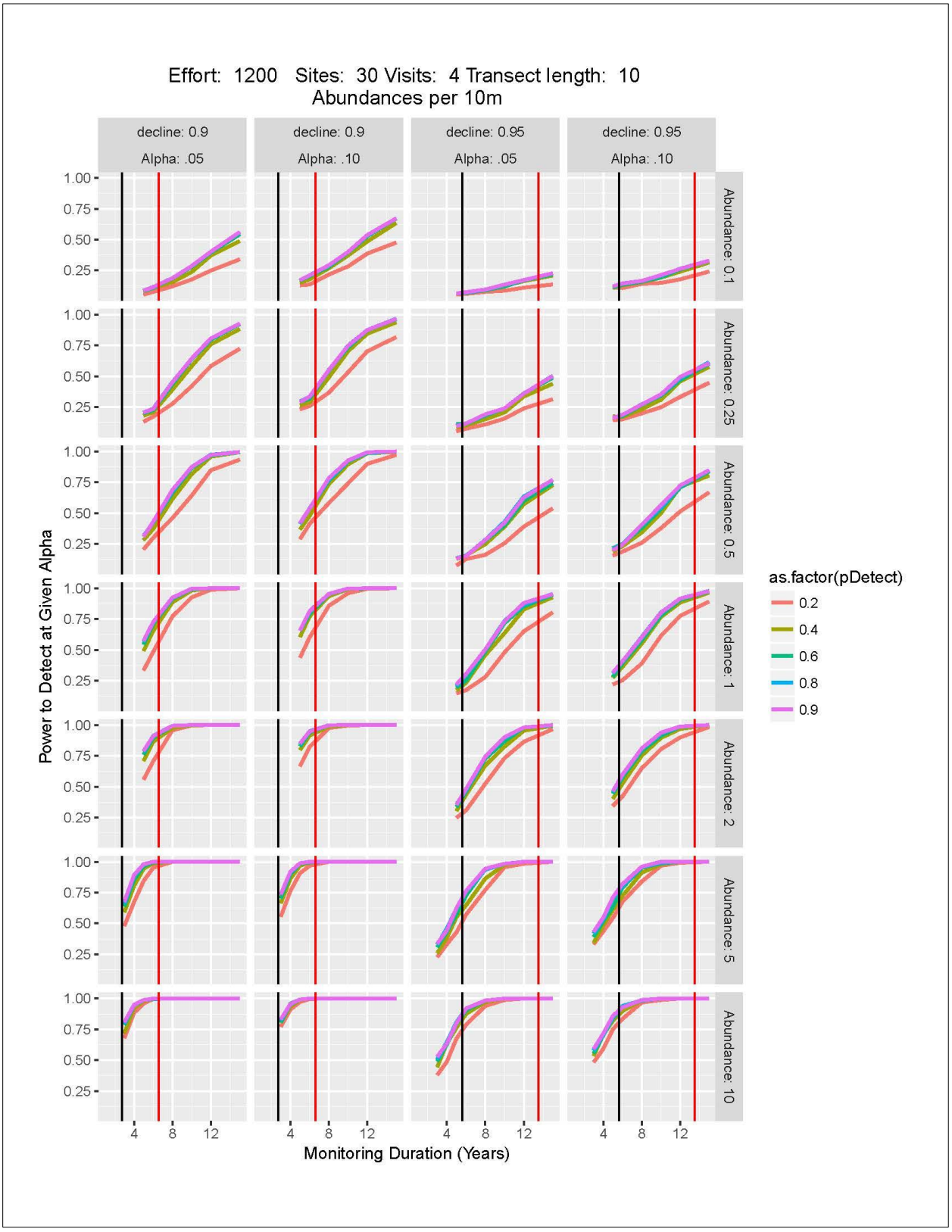


Figure A5-11. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 1200; Sites: 30; Visits: 4; Transect length: 10; and Abundances per 10 meters (32.8 ft).

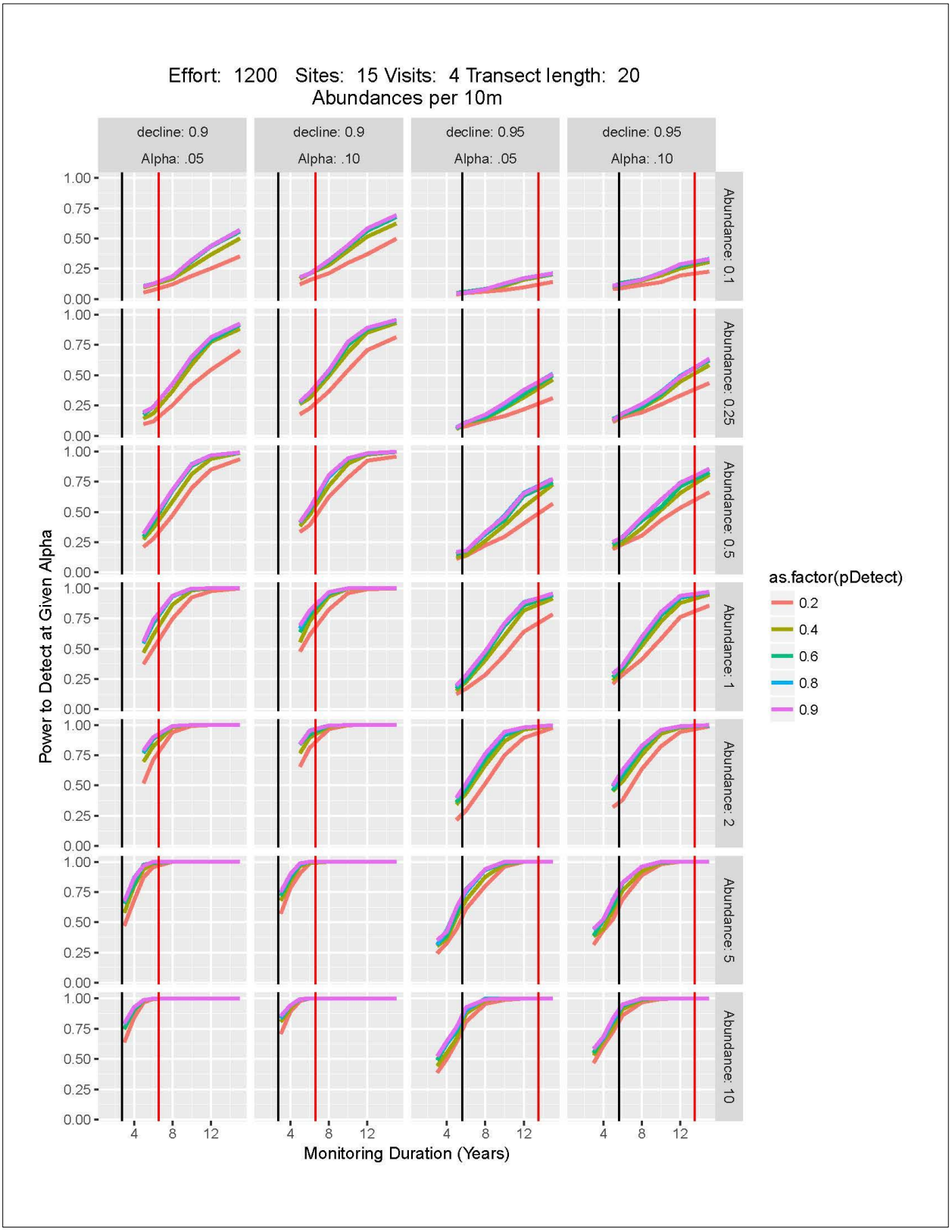


Figure A5-12. Power curves for α=0.05 and 0.10. Vertical reference lines are the time of 25% (black) and 50% (red) cumulative decrease from the initial abundances. Note that abundance values in the row faceting are per m (3.3 ft), so range from 0.1 to 2 per 10 meters (32.8 ft). Above graphs show Effort: 1200; Sites: 15; Visits: 4; Transect length: 20; and Abundances per 10 meters.

When considering trend detection, power is not the only important factor. Understanding the suitability of an analytical approach for trend detection should also consider both the bias of the estimates and the coverage of the confidence intervals or estimated uncertainty about those estimates.

Biased estimates are systematically or on average over- or under- estimates of the true values. Because bias is a property of estimates averaged across many trials, it cannot be estimated from a single real dataset, but is easy to extract from multiple simulations. For these hierarchical *N*-mixture models, the trend estimates are essentially unbiased. The mean and median of the estimates were very close to the simulated values for all parameter combinations. The clearest visualization of the lack of bias involves probability density distributions of estimate values. Given the large number of parameter combinations, a very large number of figures are required, and given the complex nature of each figure, the resulting file is very large. Therefore, these figures are provided as a separate file in Appendix A. Each combination of total effort, transect length, the number of revisits, and true decline is presented on a separate page. Within each page, mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Within each figure, separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red).

As expected, the distributions of the estimates are rather broad for a few years of data. Over longer durations, the distributions become taller and narrower. This is the result of both accumulating more data, so sampling errors and year to year fluctuations average out and matter less, and of the cumulative change increasing in size over more years, making the change (decline) larger relative to the sampling variation and year to year fluctuations. However, all distributions are centered on the true values.

The final aspect of the trend simulations worth noting is the coverage of the confidence intervals about the estimates. Coverage is the probability the true trend slope is included in the confidence intervals about the estimates. By definition, 95% of the 95% confidence intervals should include the true value. If a lower fraction of the confidence intervals contain the true value, the confidence intervals are unrealistically narrow and underestimate the uncertainty about the estimates. If a larger fraction of the confidence intervals contain the true values, the confidence intervals are too wide.

Figures A6-1 through A6-6 show that for low abundance species, the wide confidence intervals about the estimates are close to the nominal 95% coverage. However, at higher abundances and four instead of two visits, the coverages can be well below 50%. Higher detection probabilities have worse coverage, and there is a slight trend for increasing numbers of years to improve the coverage of the confidence intervals.

To some extent, these extremely poor confidence intervals reflect the simplistic approach to parametric, large-sample, normal-theory confidence intervals currently available for unmarked model results. Such simple approaches to confidence intervals often fail for mixed models, generalized linear models, adaptive cluster sampling, and other complex estimators. As for those situations, parametric bootstrap or other more complex approaches may produce confidence intervals with much better coverage.

However, the poor normal-theory confidence intervals are also a red flag for simplistic significance testing of trend estimates. Figures not present here (available upon request) confirm that half of the

failed confidence intervals were overestimates of the rate of decline, where the 95% confidence interval for that estimate only included rates of decline faster than the true value.

While I did not run simulations with no change, these results indicate that substantially more than 5% of such runs would falsely detect temporal trends at $p<0.05$ significance level. Again, more complex and reliable significance tests are possible, but they are not currently available in the unmarked R package, and they may require substantial effort to develop and test.

Finally, the failure of the confidence intervals suggests that the results of the power analyses are not to be believed. A substantial fraction of the "significant" results were produced by the over-confidence in the parameter estimates. Improved, reliable significance testing would have lower power to detect trends for any given parameter combination with fractional power, and that reduction in power would be greatest for the most abundant and detectable species. Many of the combinations with essentially 100% power would still have essentially 100% power.

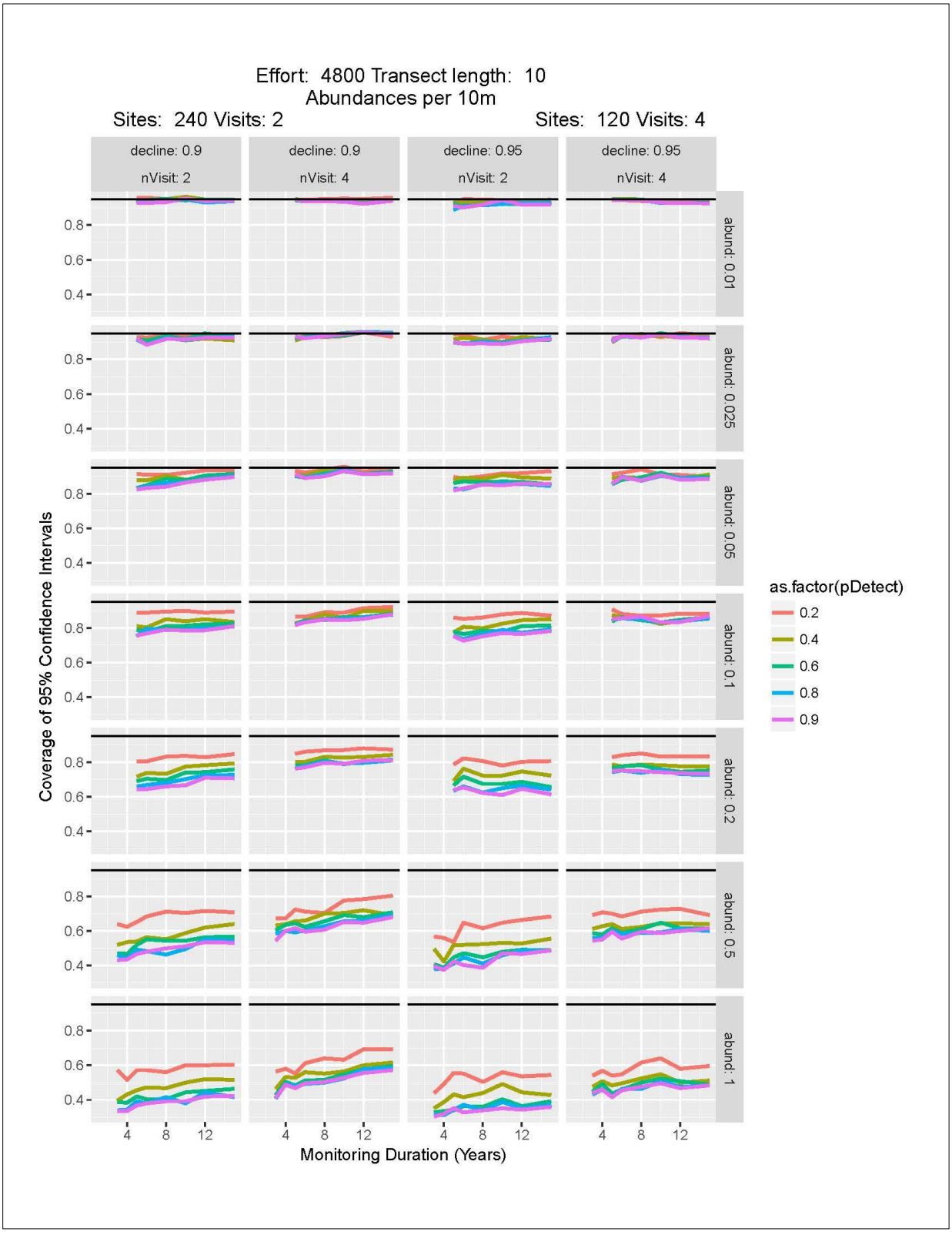


Figure A6-1. Coverage of the 95% confidence intervals for the estimated temporal trends. The Y axis is the fraction of the simulations with that set of parameter values that generated 95% confidence intervals for the temporal trend that included the true (simulated) value. Values near 0.95 are good. Values above .095 reflect overly conservative confidence intervals. Values below 0.95 reflect overly aggressive (overconfident) confidence intervals suggesting that the estimates are more accurate than they actually are. Above graphs show Effort: 4800; Transect Length: 10; and Abundances per 10 meters (32.8 ft).

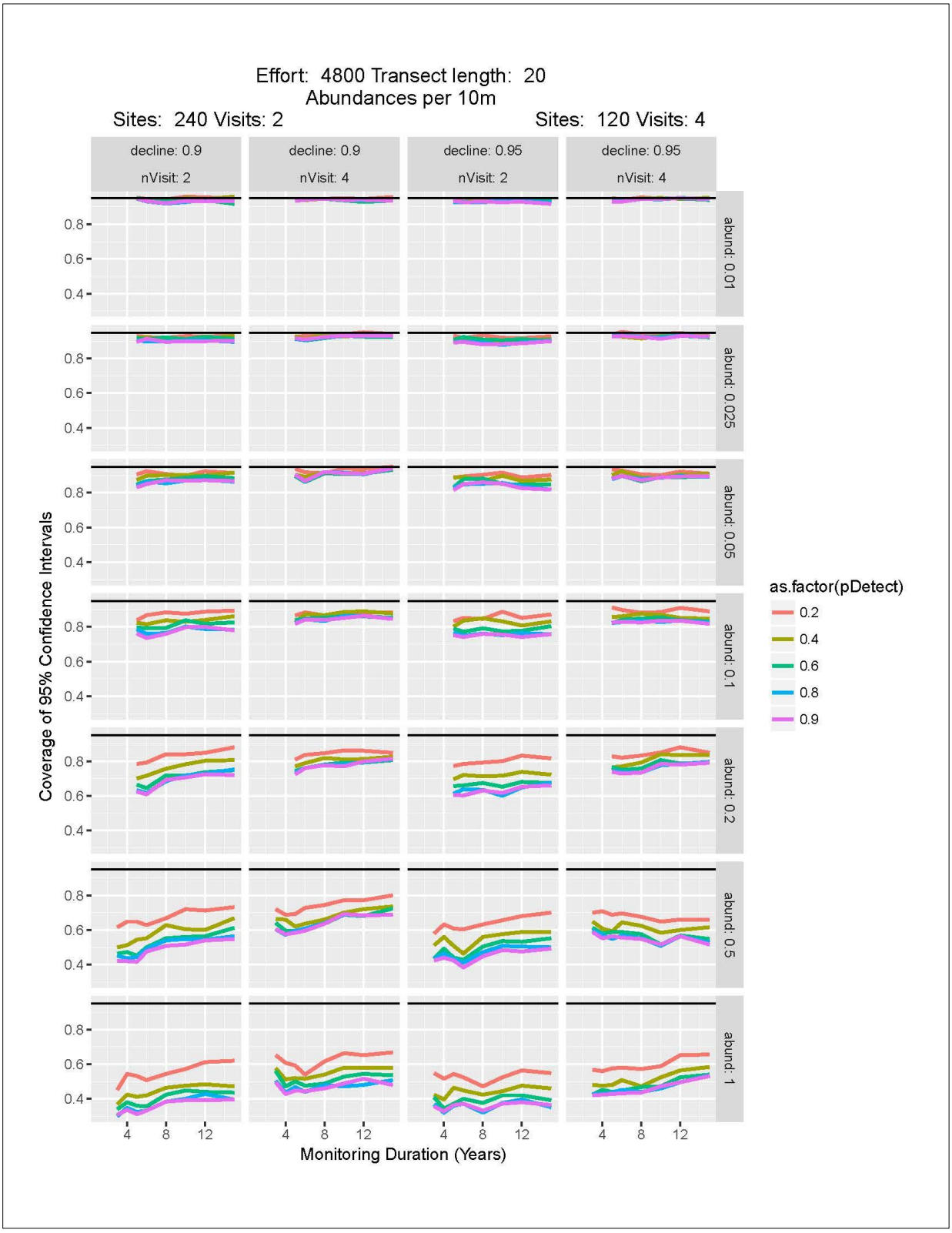


Figure A6-2. Coverage of the 95% confidence intervals for the estimated temporal trends. The Y axis is the fraction of the simulations with that set of parameter values that generated 95% confidence intervals for the temporal trend that included the true (simulated) value. Values near 0.95 are good. Values above .095 reflect overly conservative confidence intervals. Values below 0.95 reflect overly aggressive (overconfident) confidence intervals suggesting that the estimates are more accurate than they actually are. Above graphs show Effort: 4800; Transect Length: 20; and Abundances per 10 meters (32.8 ft).

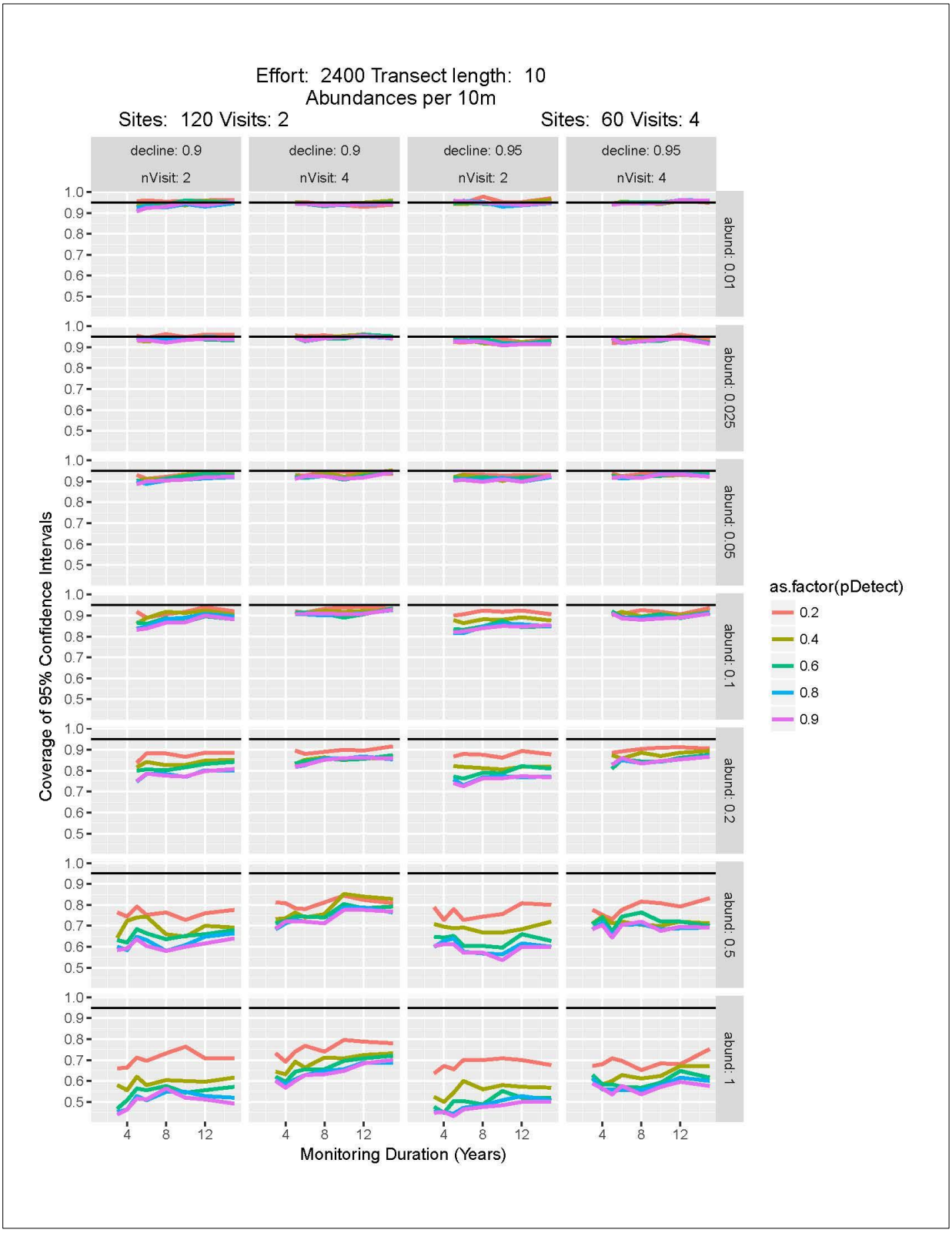


Figure A6-3. Coverage of the 95% confidence intervals for the estimated temporal trends. The Y axis is the fraction of the simulations with that set of parameter values that generated 95% confidence intervals for the temporal trend that included the true (simulated) value. Values near 0.95 are good. Values above .095 reflect overly conservative confidence intervals. Values below 0.95 reflect overly aggressive (overconfident) confidence intervals suggesting that the estimates are more accurate than they actually are. Above graphs show Effort: 2400; Transect Length: 10; and Abundances per 10 meters (32.8 ft).

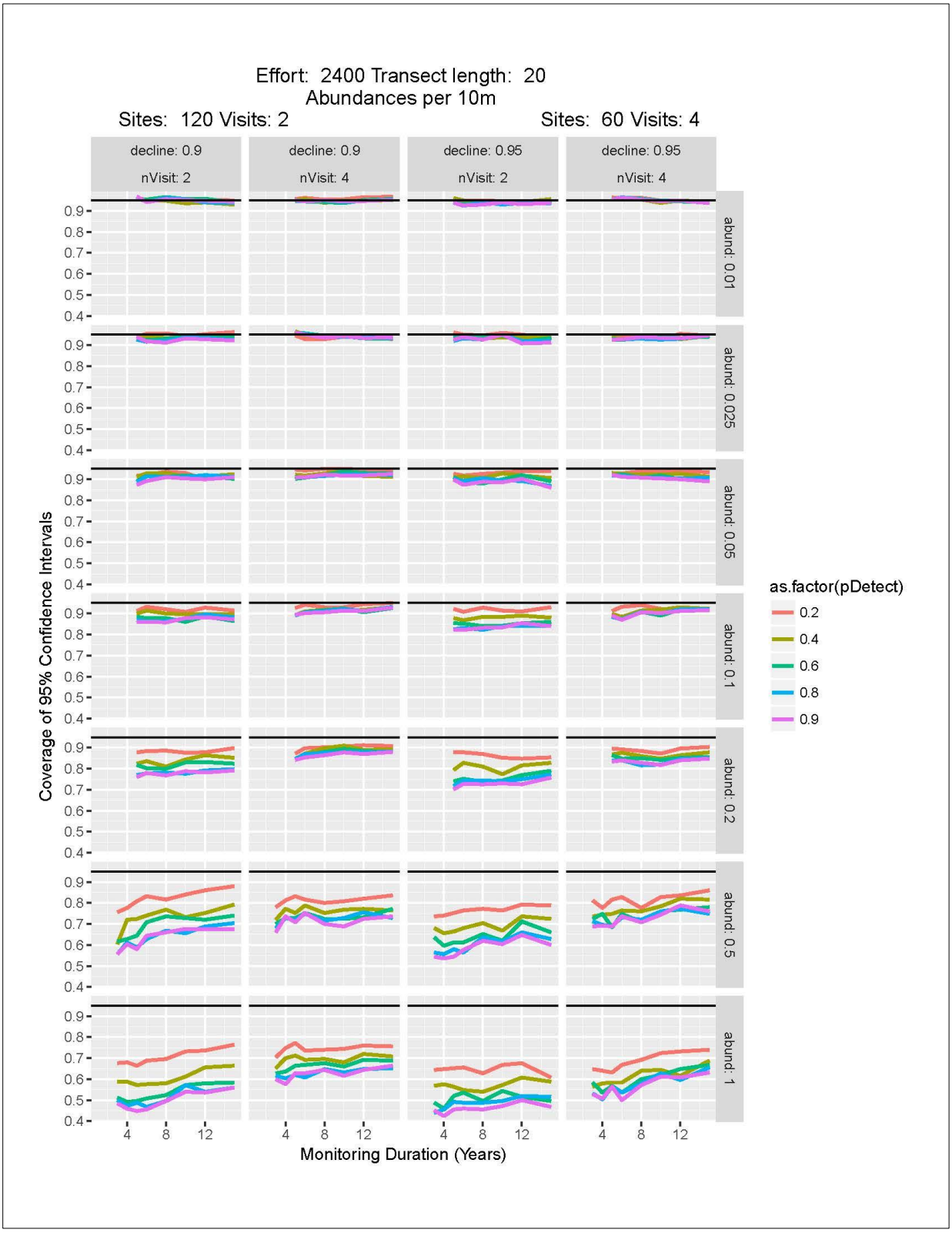


Figure A6-4. Coverage of the 95% confidence intervals for the estimated temporal trends. The Y axis is the fraction of the simulations with that set of parameter values that generated 95% confidence intervals for the temporal trend that included the true (simulated) value. Values near 0.95 are good. Values above .095 reflect overly conservative confidence intervals. Values below 0.95 reflect overly aggressive (overconfident) confidence intervals suggesting that the estimates are more accurate than they actually are. Above graphs show Effort: 2400; Transect Length: 20; and Abundances per 10 meters (32.8 ft).

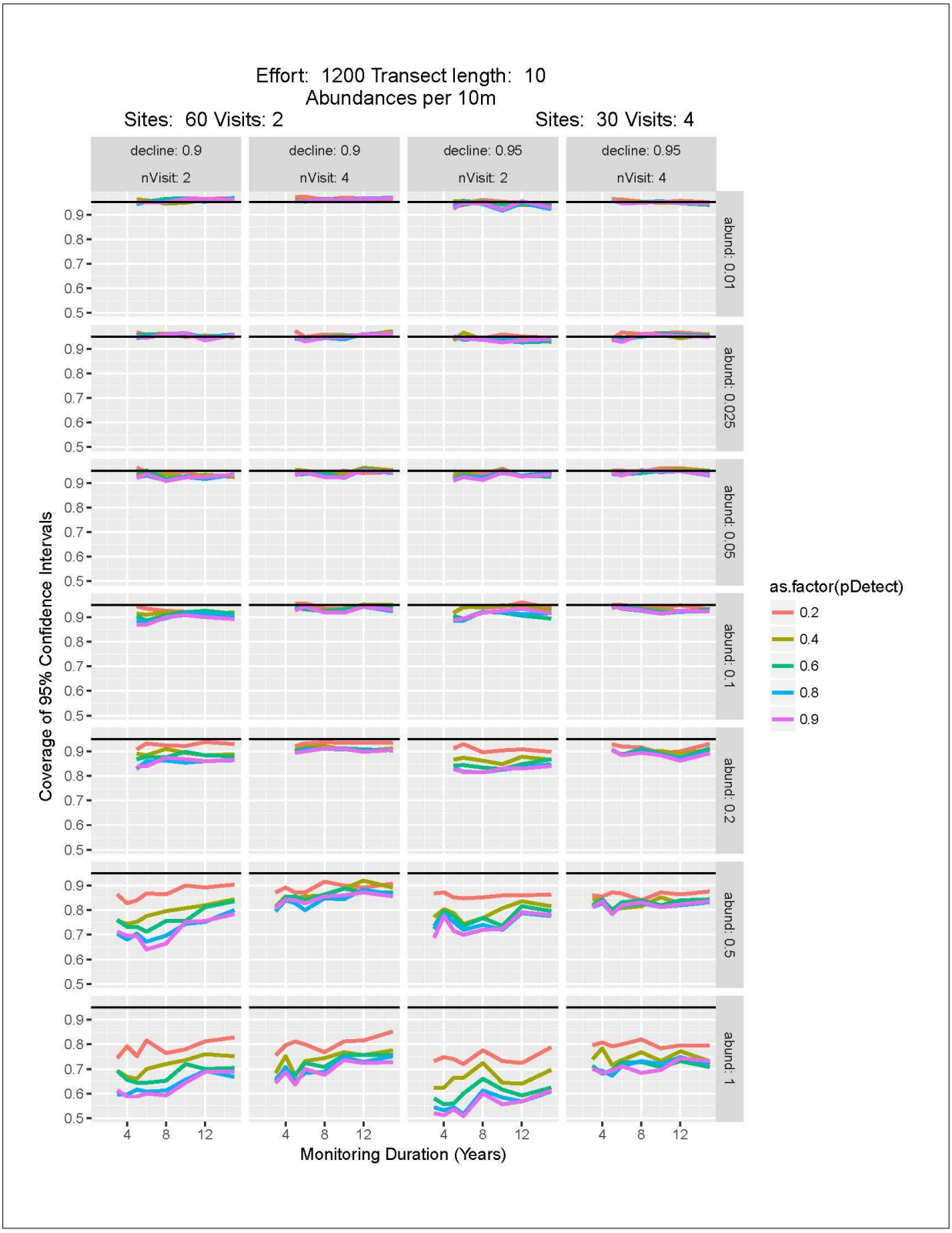


Figure A6-5. Coverage of the 95% confidence intervals for the estimated temporal trends. The Y axis is the fraction of the simulations with that set of parameter values that generated 95% confidence intervals for the temporal trend that included the true (simulated) value. Values near 0.95 are good. Values above .095 reflect overly conservative confidence intervals. Values below 0.95 reflect overly aggressive (overconfident) confidence intervals suggesting that the estimates are more accurate than they actually are. Above graphs show Effort: 1200; Transect Length: 10; and Abundances per 10 meters (32.8 ft).

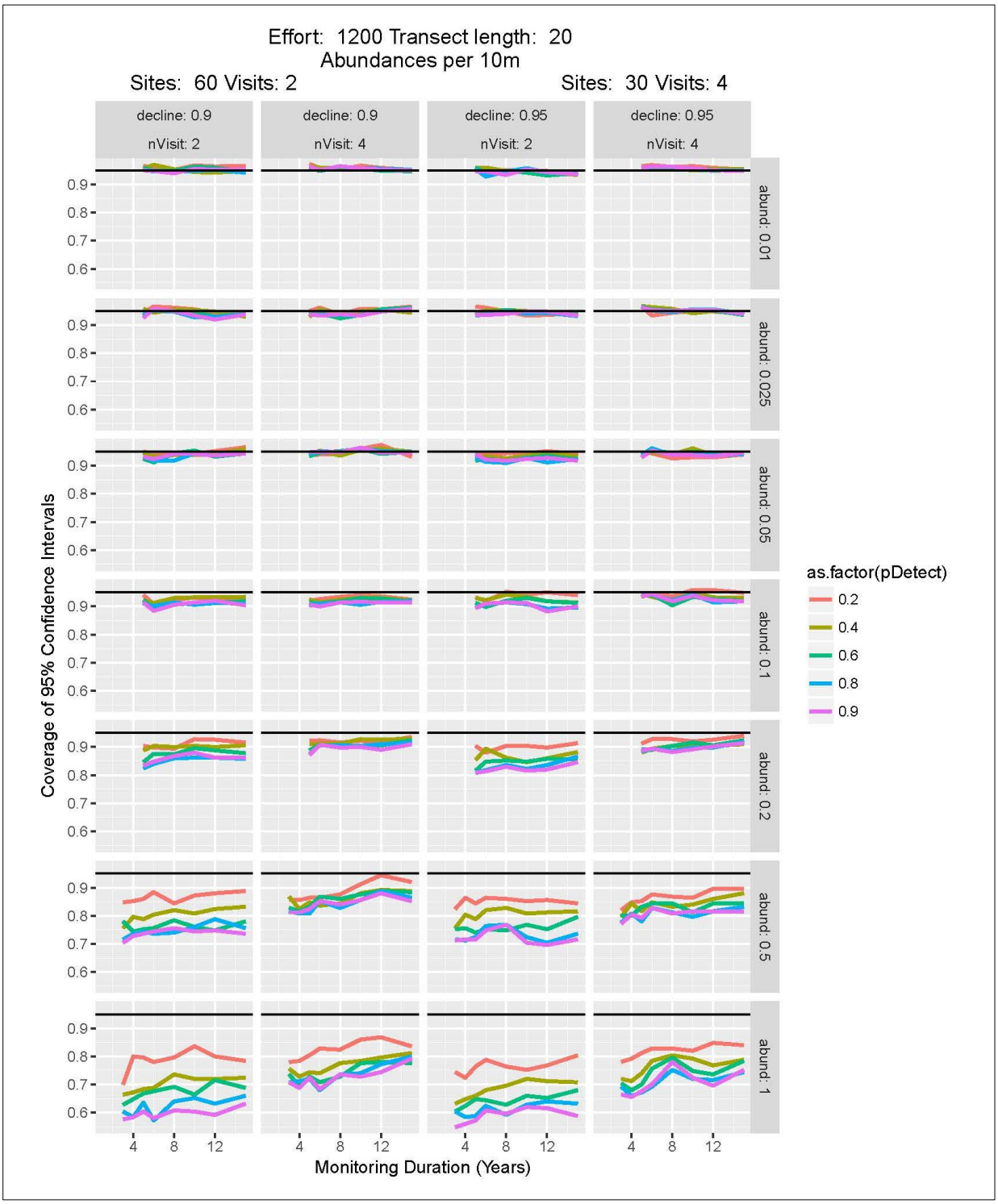


Figure A6-6. Coverage of the 95% confidence intervals for the estimated temporal trends. The Y axis is the fraction of the simulations with that set of parameter values that generated 95% confidence intervals for the temporal trend that included the true (simulated) value. Values near 0.95 are good. Values above .095 reflect overly conservative confidence intervals. Values below 0.95 reflect overly aggressive (overconfident) confidence intervals suggesting that the estimates are more accurate than they actually are. Above graphs show Effort: 1200; Transect Length: 20; and Abundances per 10 meters (32.8 ft).

Conclusions

These results are not an argument against monitoring cave aquatic biota. If cave aquatic biota are a high enough priority for park resource management, they might well be worth allocating more effort toward, or developing other methods. In addition, as noted in Taylor and Gerrodette (1993) there may be good reasons to undertake surveys even with low power to detect modest declines.

Second, these results are not an argument for ignoring imperfect detection and instead performing simple tests for trends in uncorrected numbers of individuals observed. While several authors argue against complex models attempting to correct for imperfect detection, none of them apply to monitoring for trends in abundances. Hutto and Young (2003) and Hutto (2016) argue for fixed-radius plots as population indices rather than distance-sampling-based corrections for imperfect detection. Welsh et al. (2013) argue against correcting for imperfect detection in occupancy models, but do not consider abundance estimates, let alone monitoring for temporal trends. Guillera-Arroita et al. (2014) effectively rebut most of the Welsh et al. (2013) arguments; the reply from Welch et al. is reduced to "we found at least one counter-example where correction for imperfect detection produces worse estimates of occupancy."

These results do argue that monitoring cave aquatic biota with the proposed methods and level of effort are unlikely to provide management-relevant information about either status or temporal trends in abundance for more than the most abundant and easiest to detect one or two species. They show that for status, it is important to adjust methods to improve detection probabilities to at least 0.4 or 0.5, with substantial benefit to increasing above that level. For the rarest species, the total abundance over the sampled area matters for both status and trend estimates. The ability to sample more meters of stream length, and thus have the possibility of detecting more than a handful of individuals, is important. Doubling the total stream length surveyed, and doubling the length of the transects, thus keeping the numbers of transects and revisits constant, is equivalent to doubling the abundance of that species. There may be allocations of that doubled effort that would improve the estimates by even more than that amount. If monitoring cave aquatic biota is valuable for park resource management, then development of methods with higher detection probabilities than visual surveys, and some way of surveying more meters of stream to encounter more individuals, are essential prior to initiating monitoring.

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Appendix A. Distributions of Trend Estimates

Each combination of total effort, transect length, the number of revisits, and true decline is presented on a separate page. Within each page, mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Within each figure, separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red).

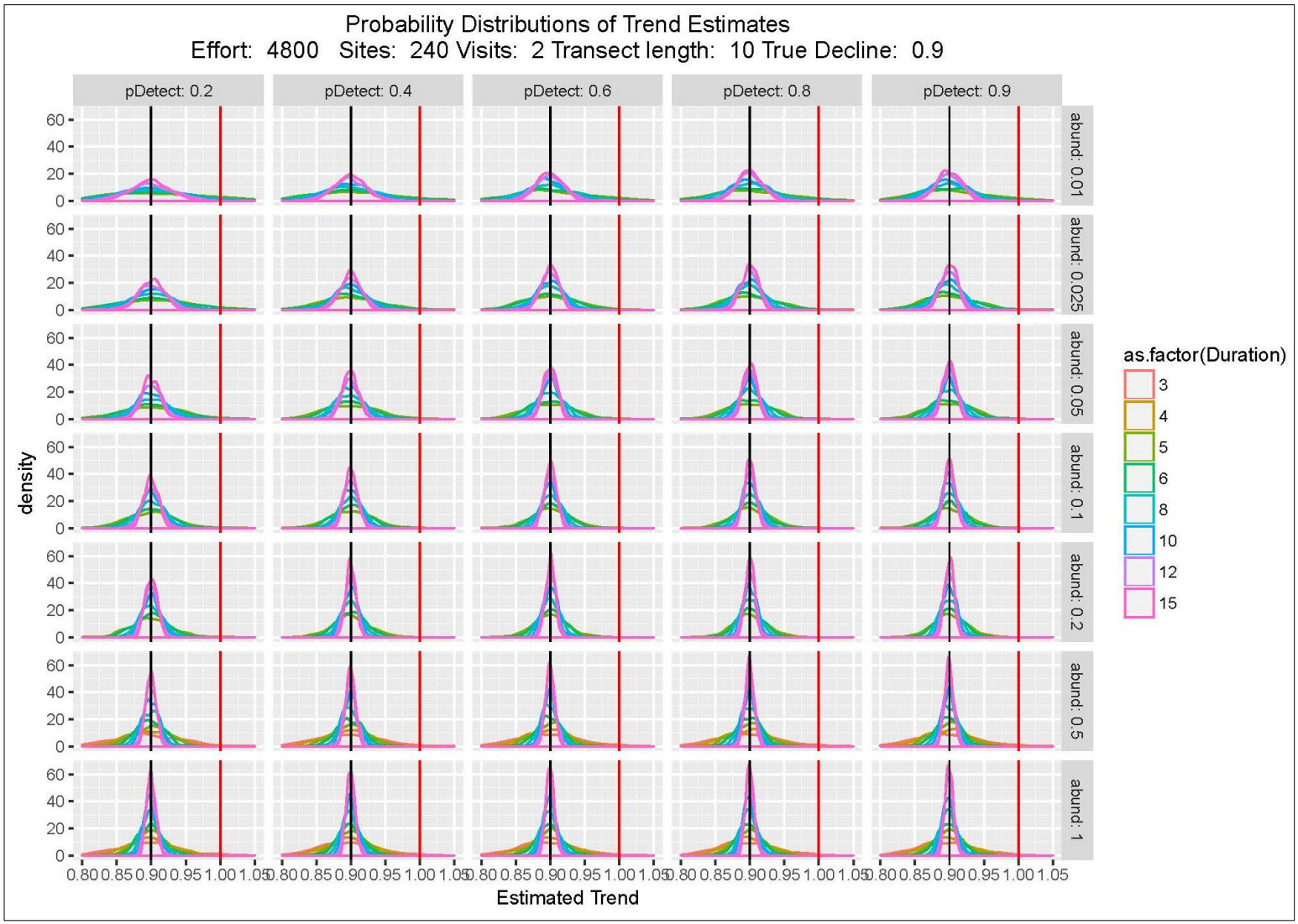


Figure A7-1. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 240; Visits: 2; Transect length: 10; and True Decline: 0.9.

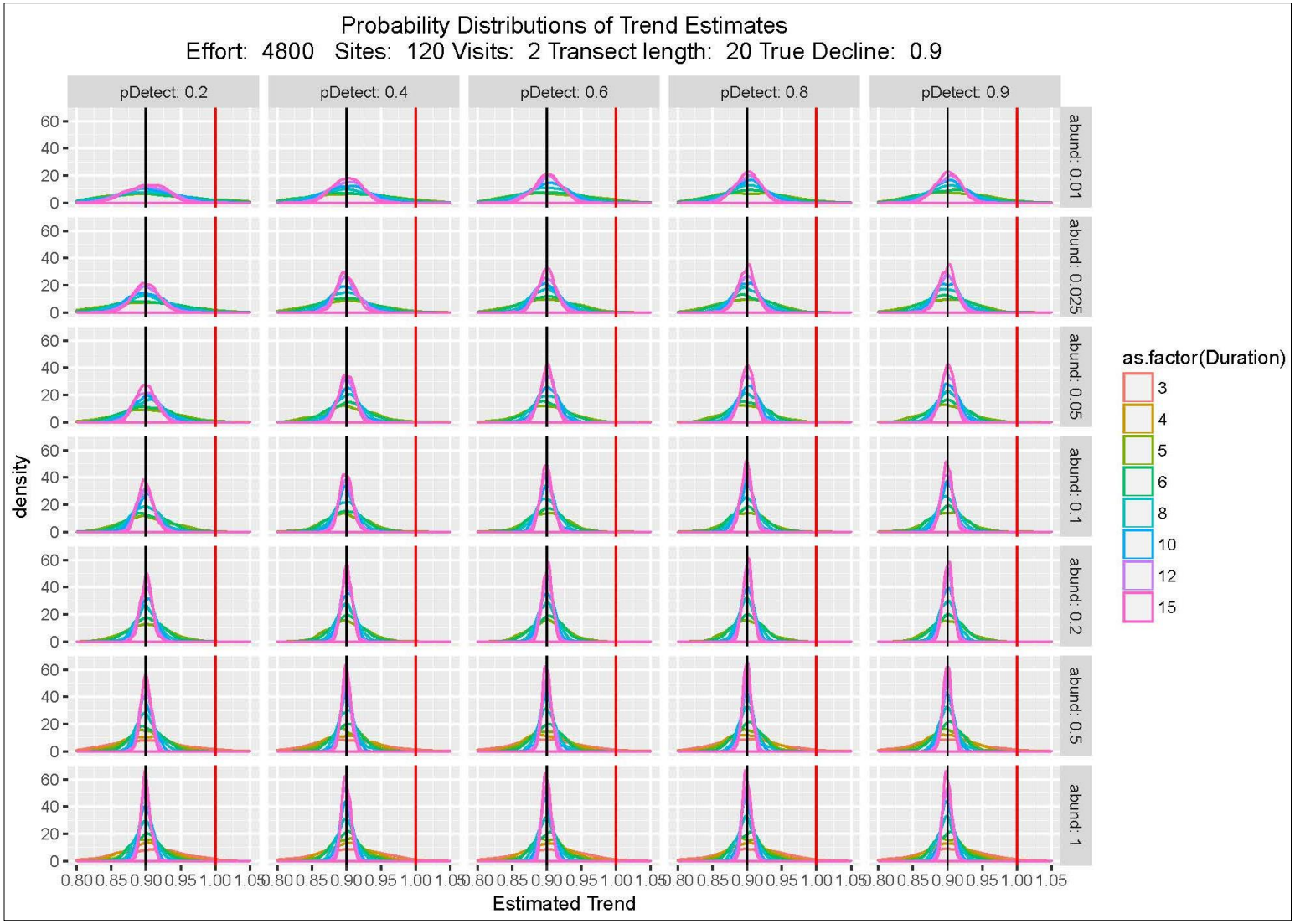


Figure A7-2. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 120; Visits: 2; Transect length: 20; and True Decline: 0.9.

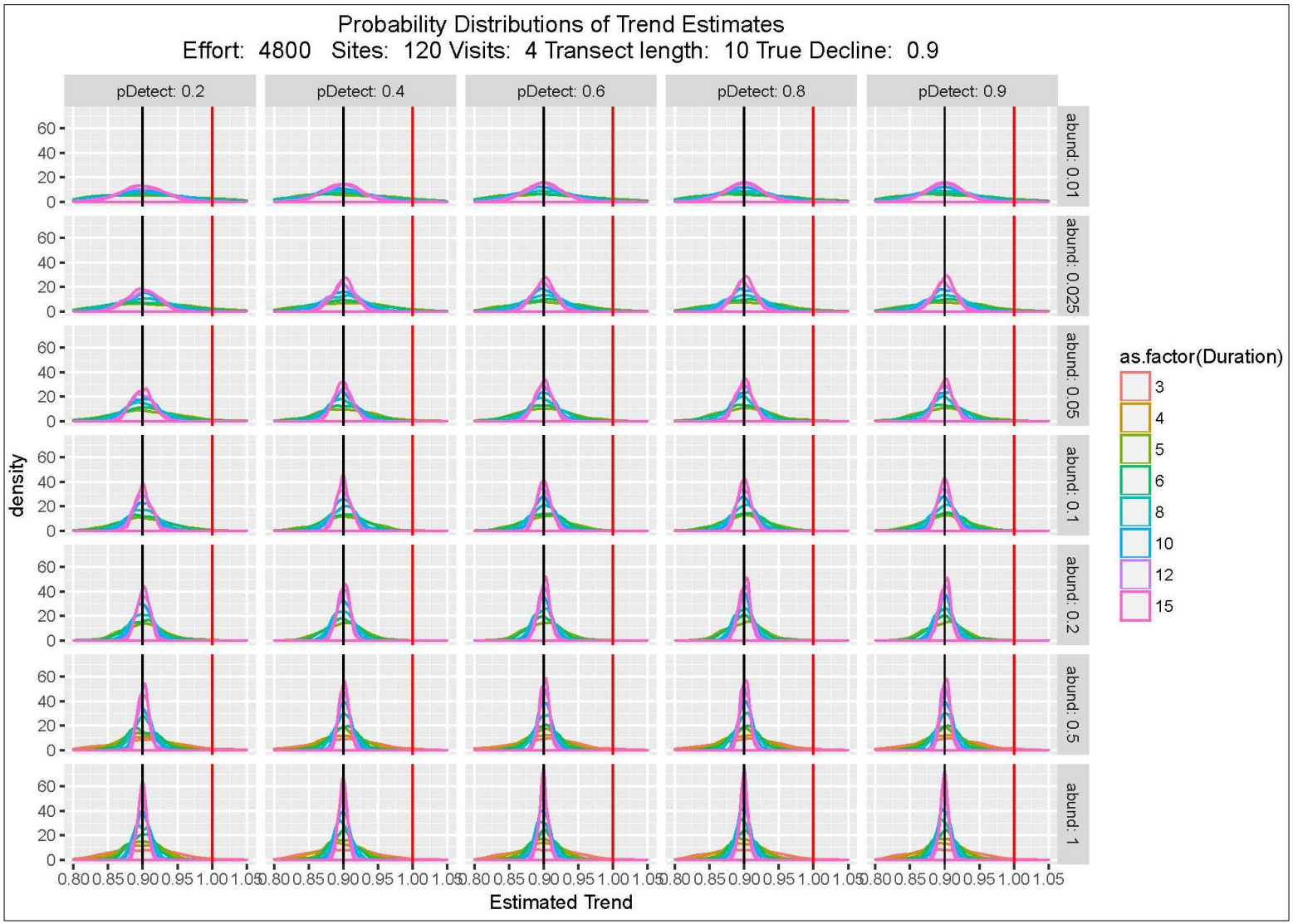


Figure A7-3. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 120; Visits: 4; Transect length: 10; and True Decline: 0.9.

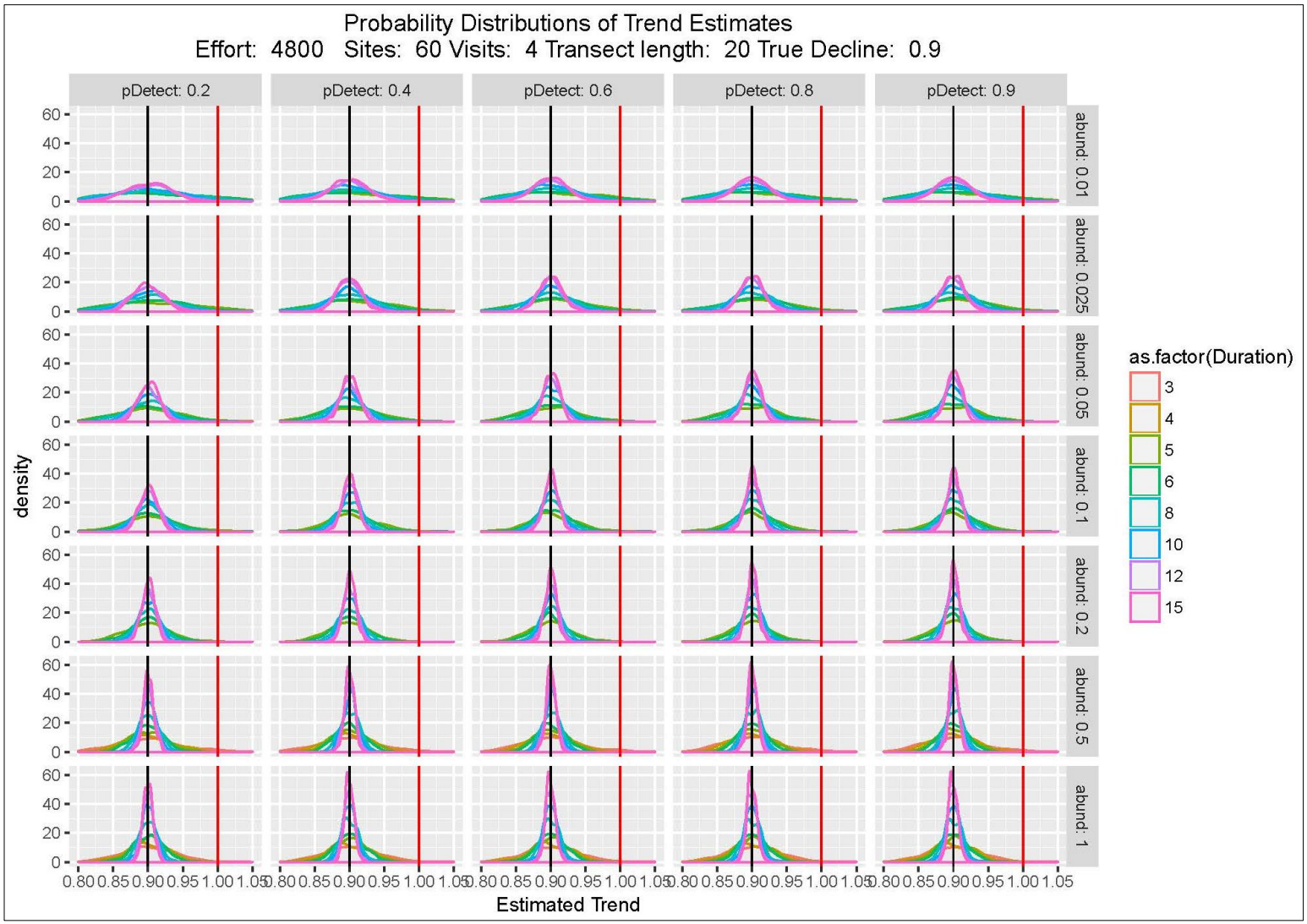


Figure A7-4. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 60; Visits: 4; Transect length: 20; and True Decline: 0.9.

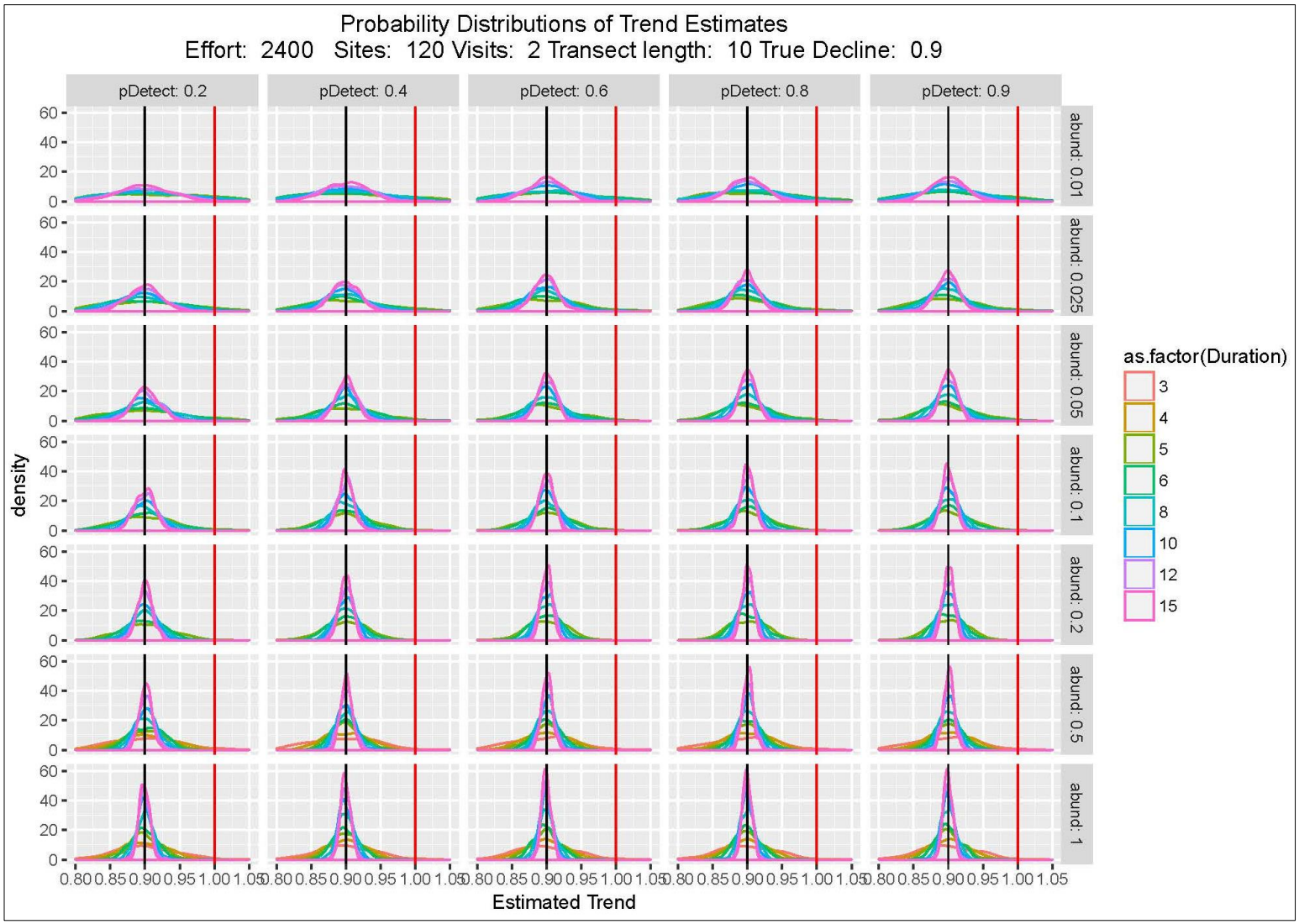


Figure A7-5. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 120; Visits: 2; Transect length: 10; and True Decline: 0.9.

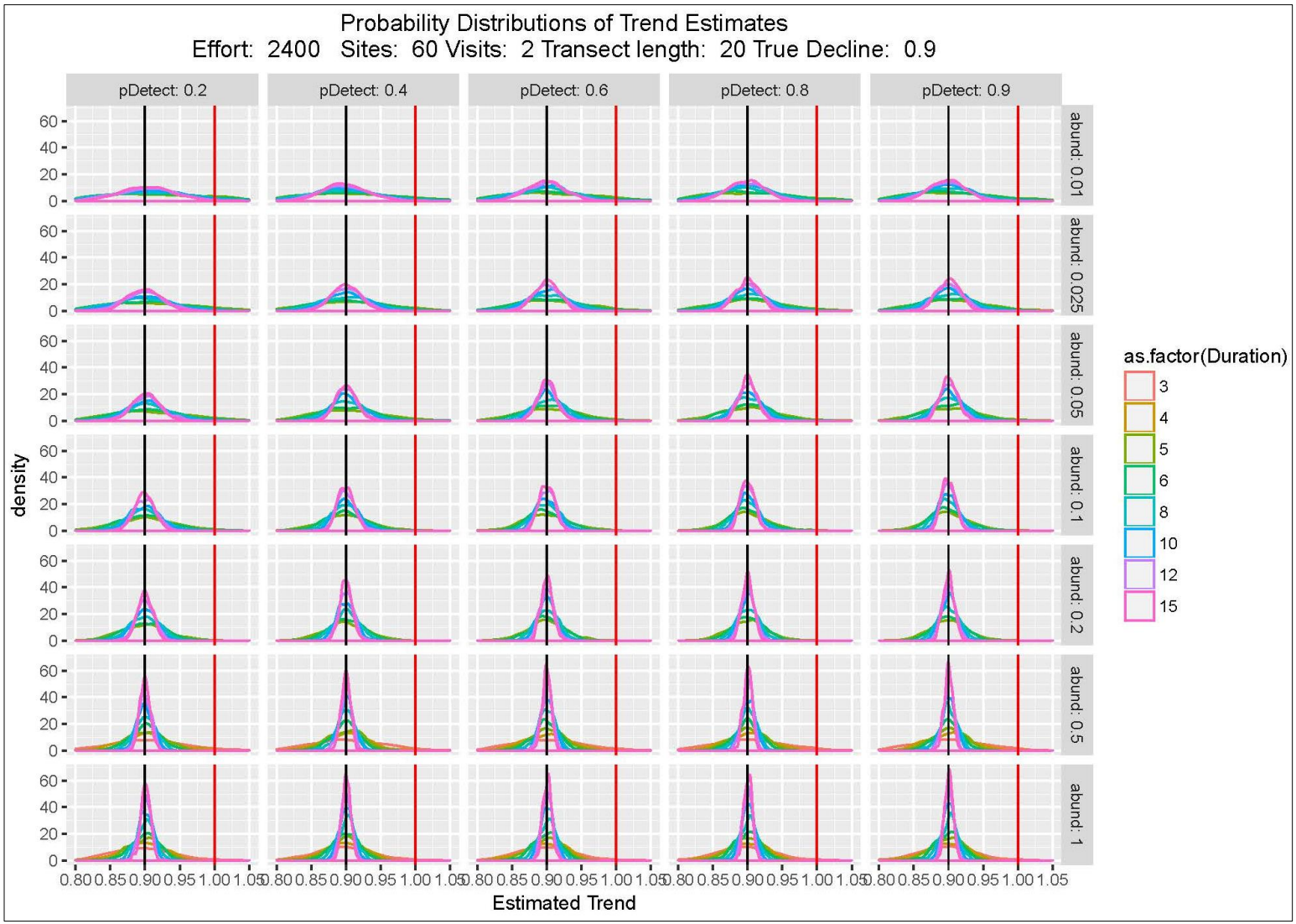


Figure A7-6. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 60; Visits: 2; Transect length: 20; and True Decline: 0.9.

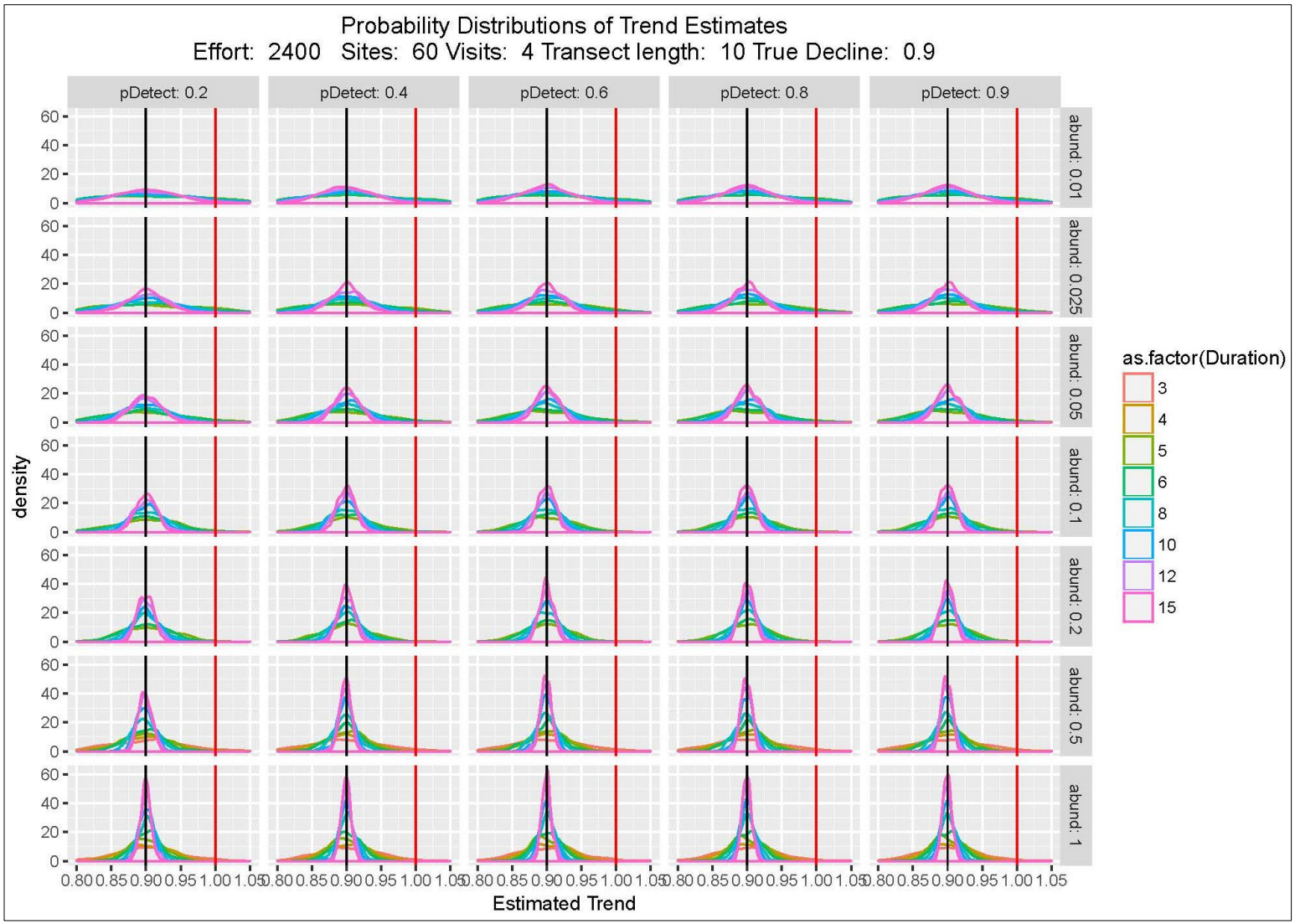


Figure A7-7. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 60; Visits: 4; Transect length: 10; and True Decline: 0.9.

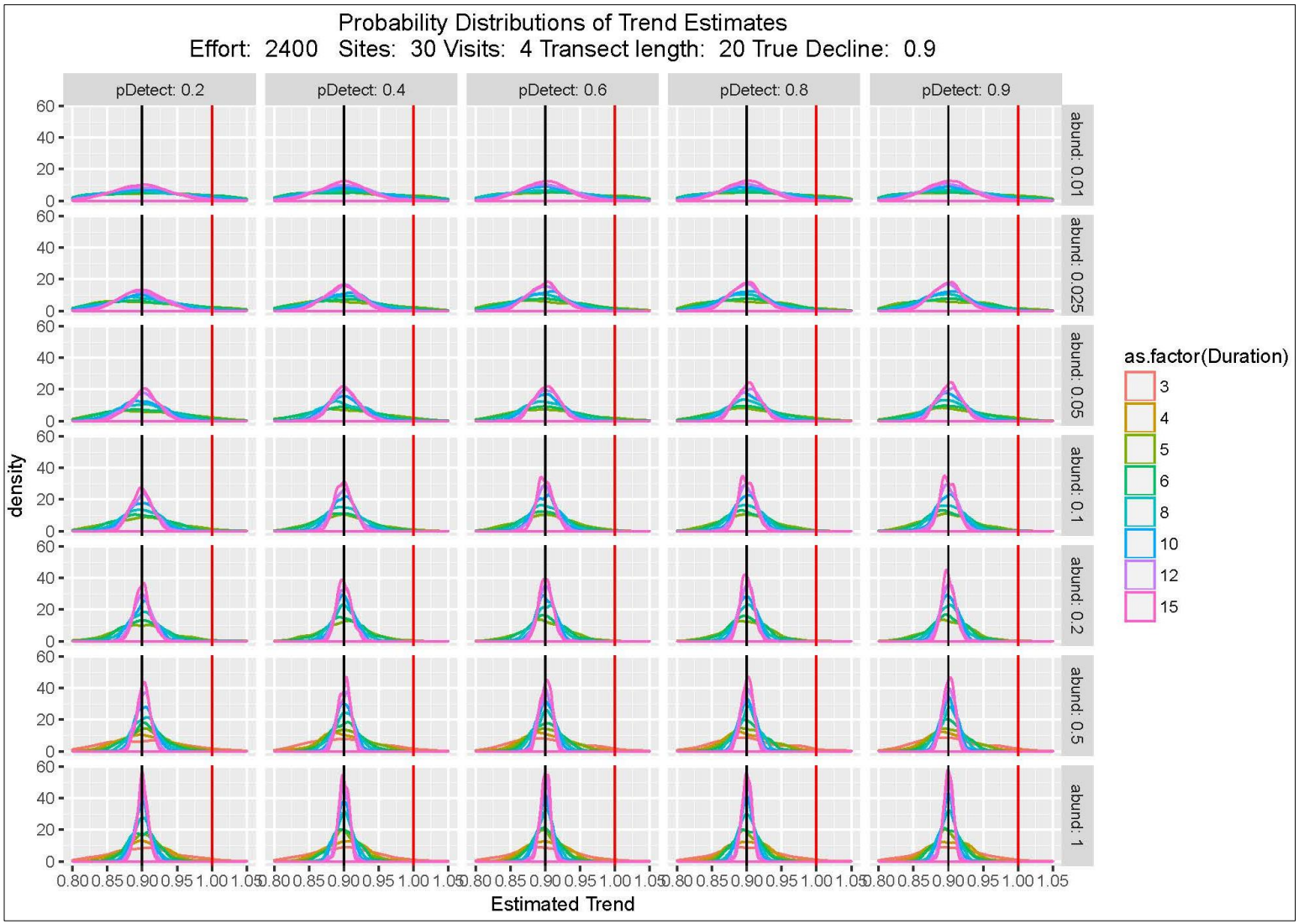


Figure A7-8. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 30; Visits: 4; Transect length: 20; and True Decline: 0.9.

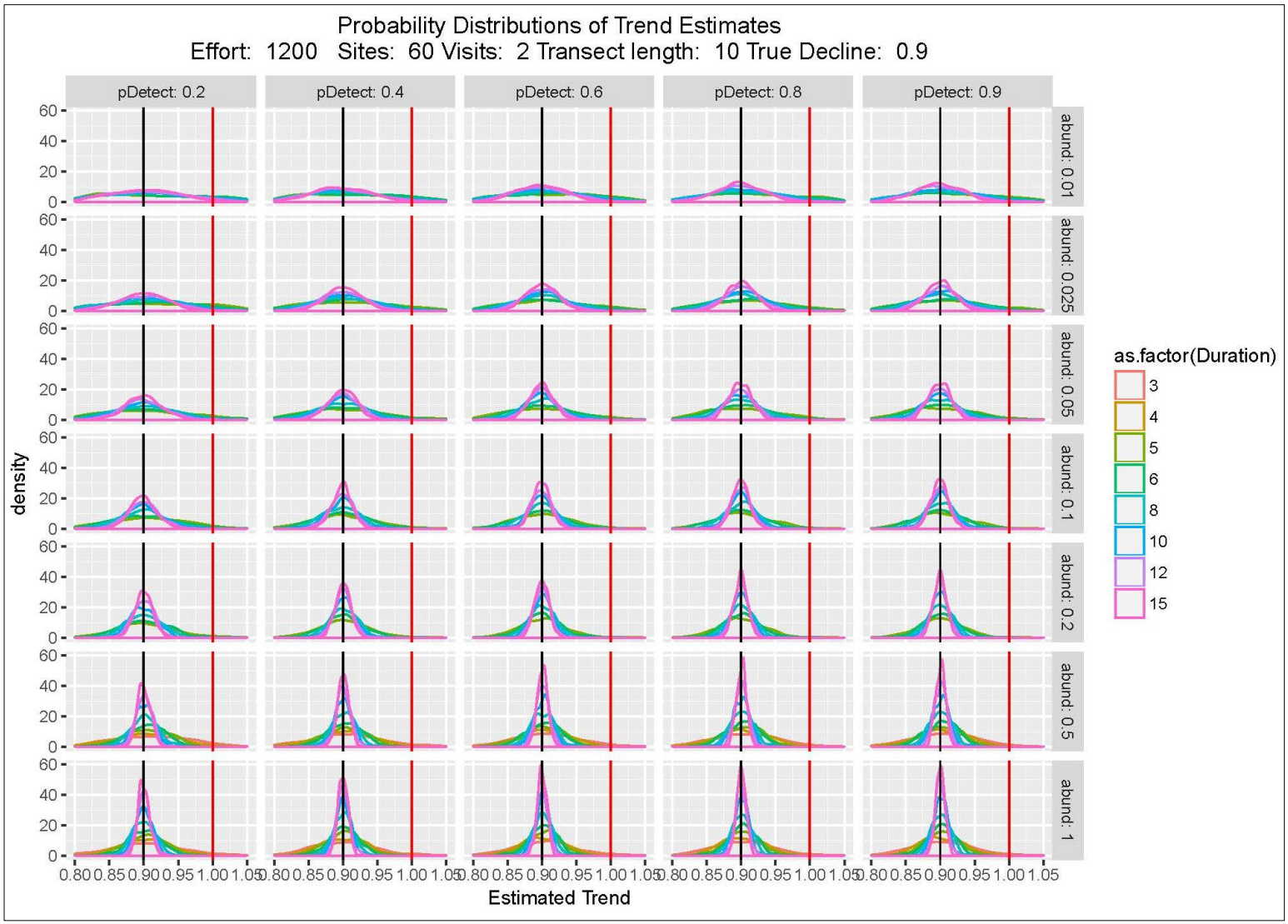


Figure A7-9. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 60; Visits: 2; Transect length: 10; and True Decline: 0.9.

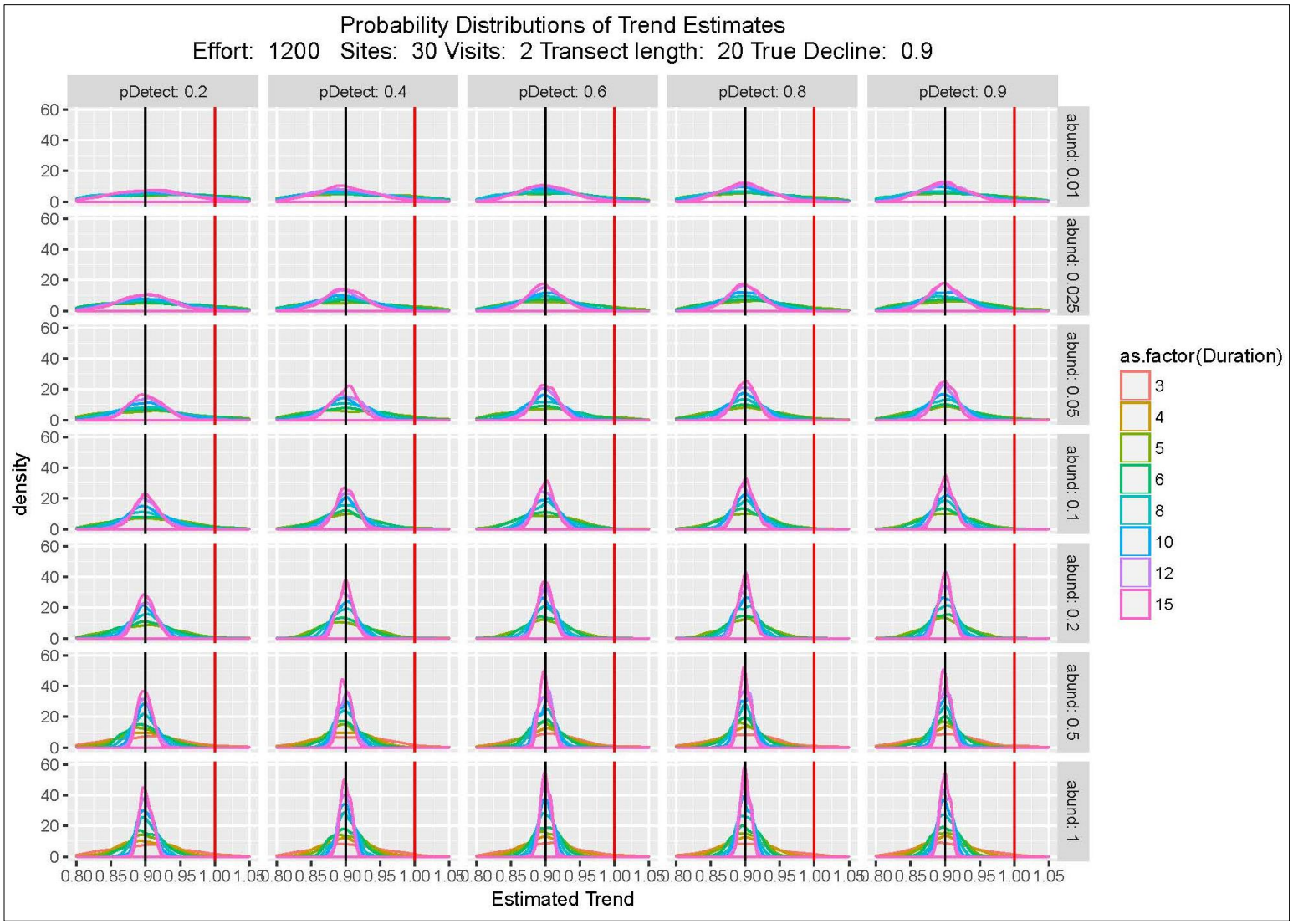


Figure A7-10. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 30; Visits: 2; Transect length: 20; and True Decline: 0.9.

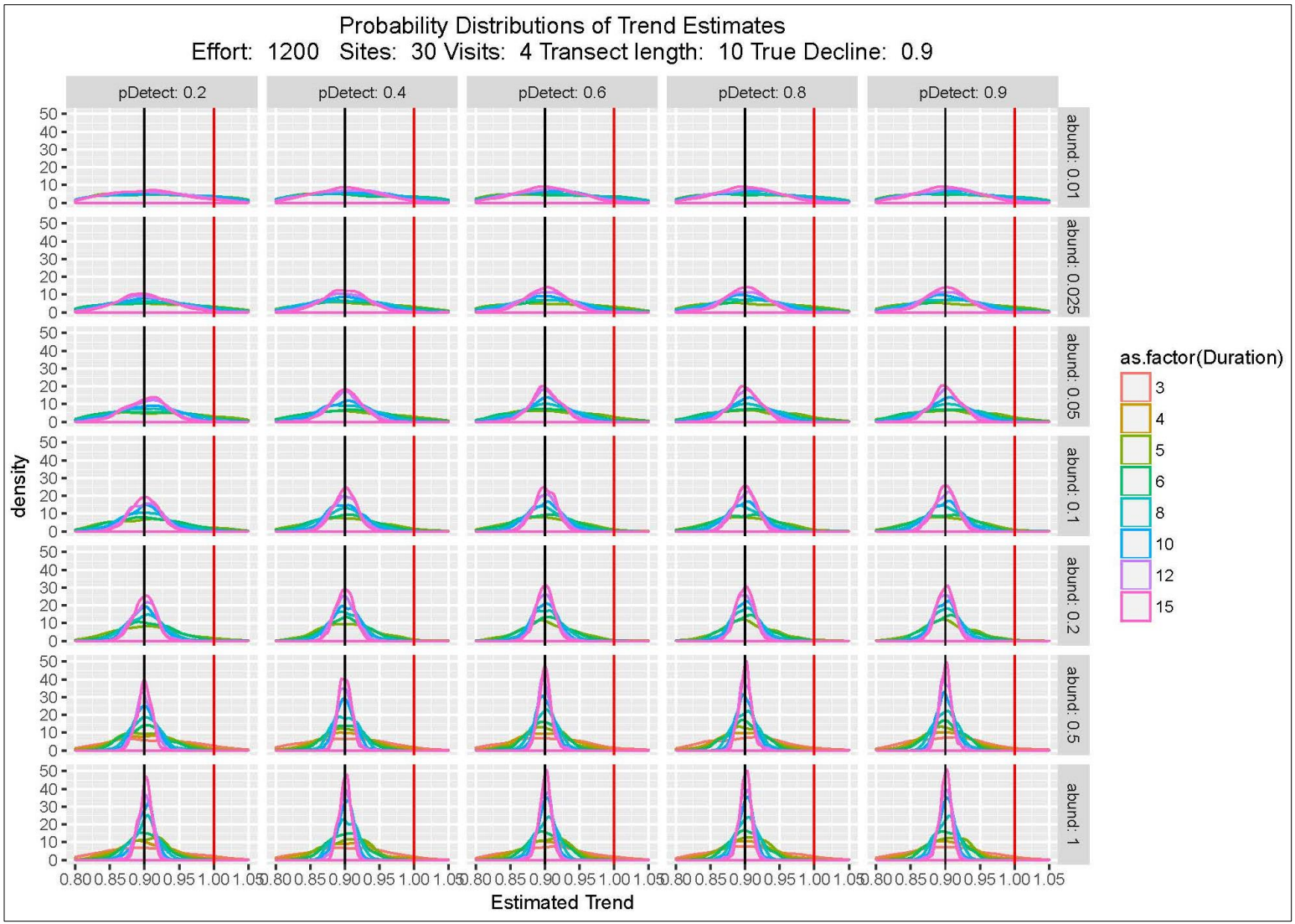


Figure A7-11. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 30; Visits: 4; Transect length: 10; and True Decline: 0.9.

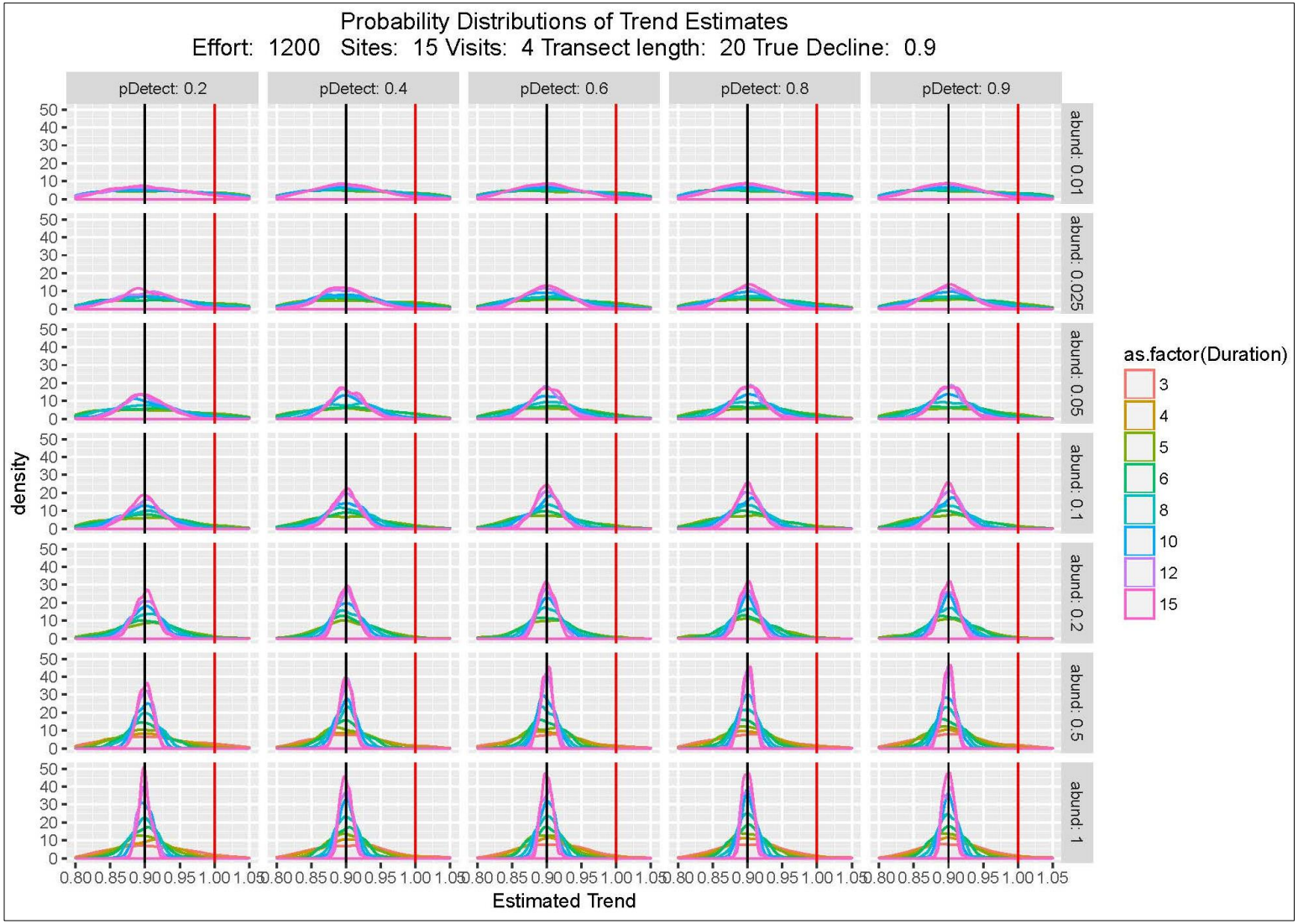


Figure A7-12. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 15; Visits: 4; Transect length: 20; and True Decline: 0.9.

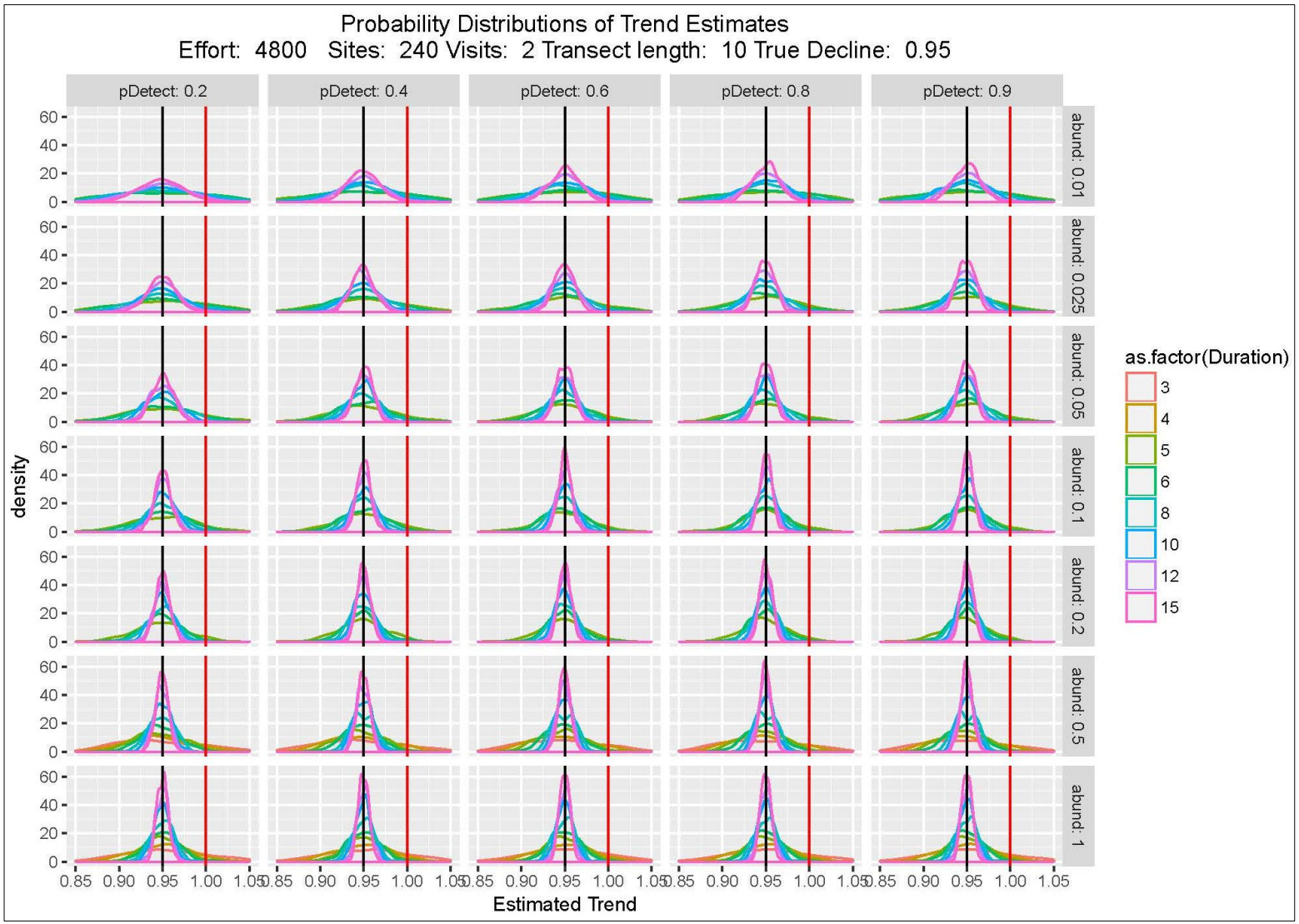


Figure A7-13. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 240; Visits: 2; Transect length: 10; and True Decline: 0.95.

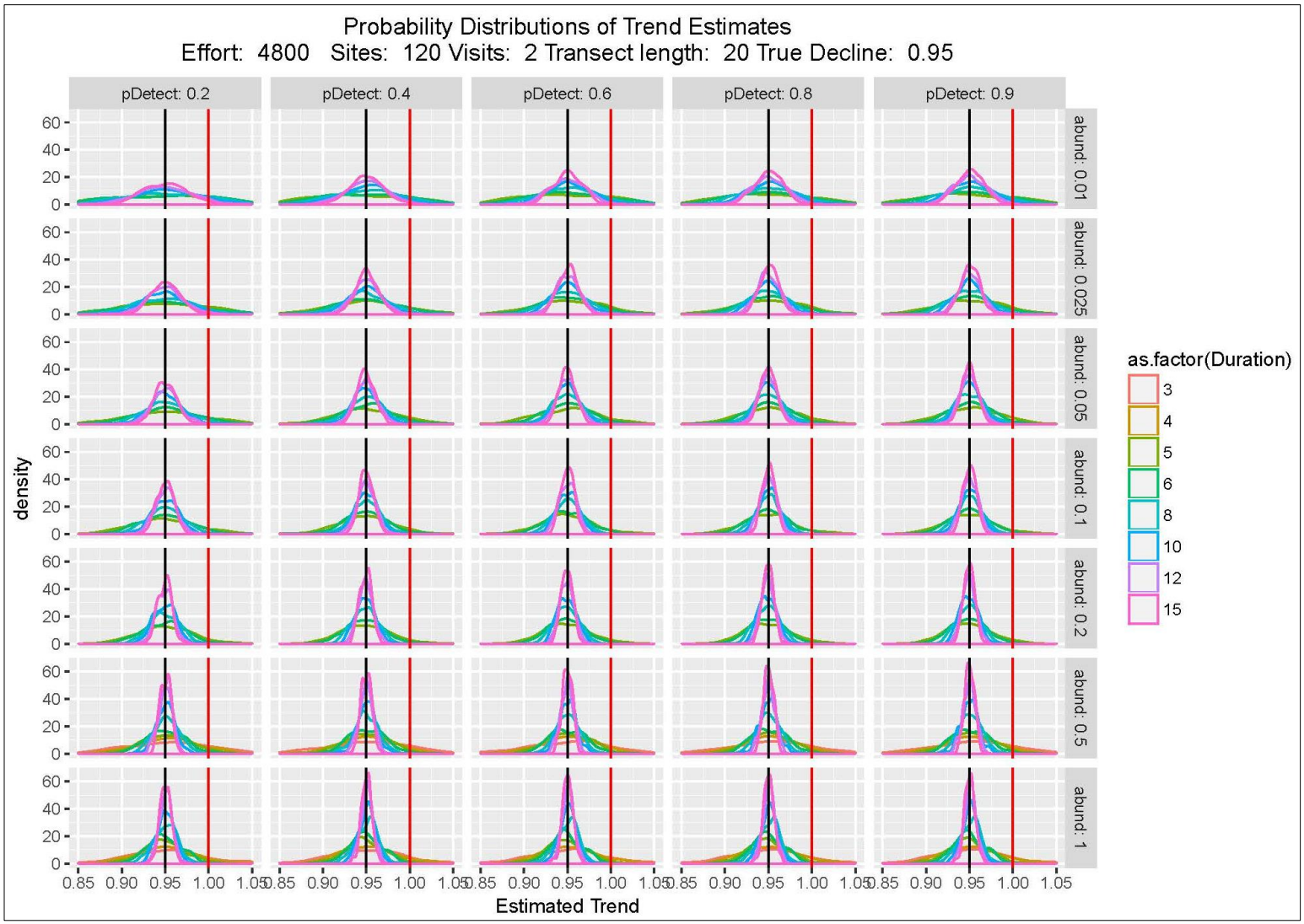


Figure A7-14. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 120; Visits: 2; Transect length: 20; and True Decline: 0.95.

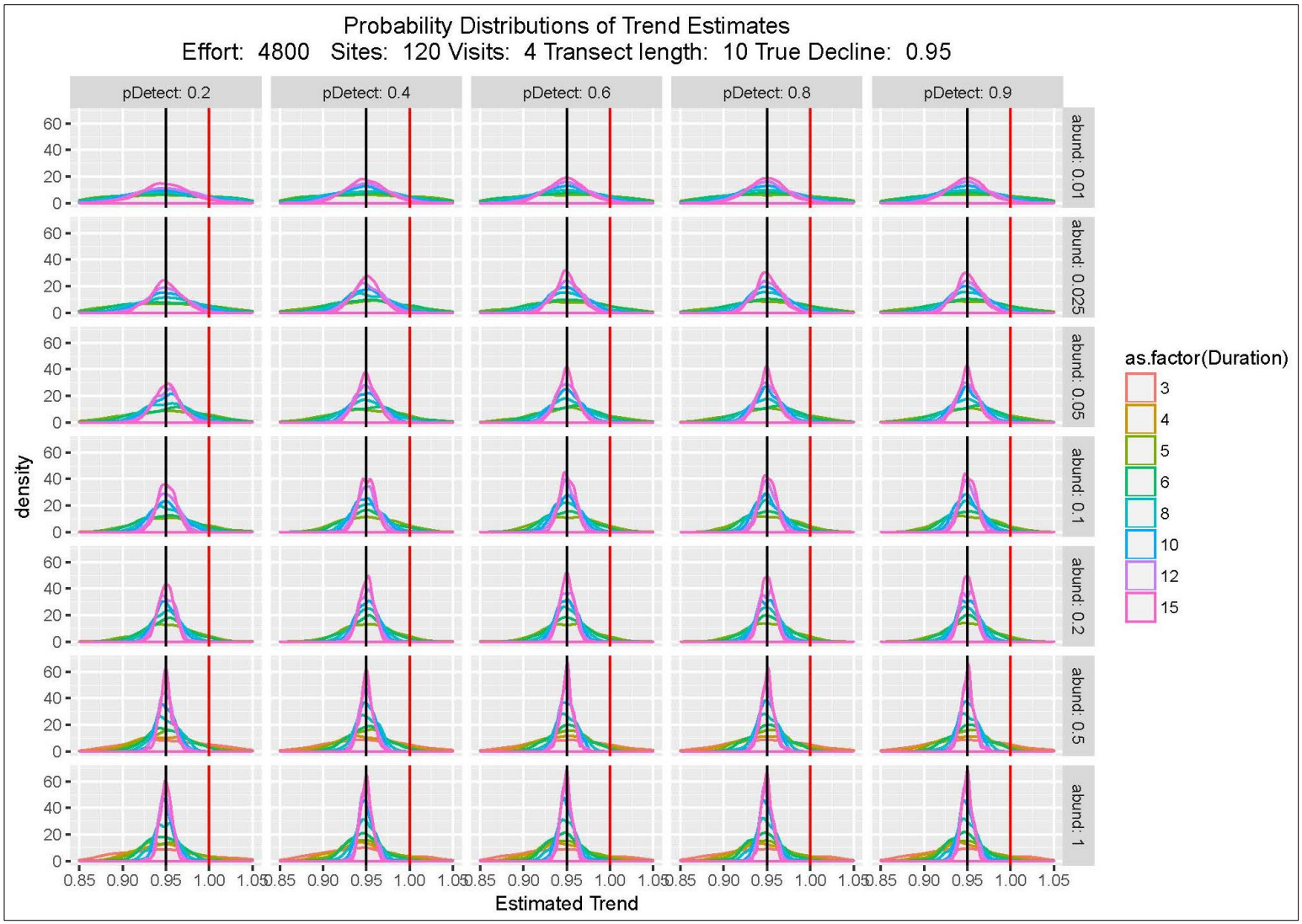


Figure A7-15. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 120; Visits: 4; Transect length: 10; and True Decline: 0.95.

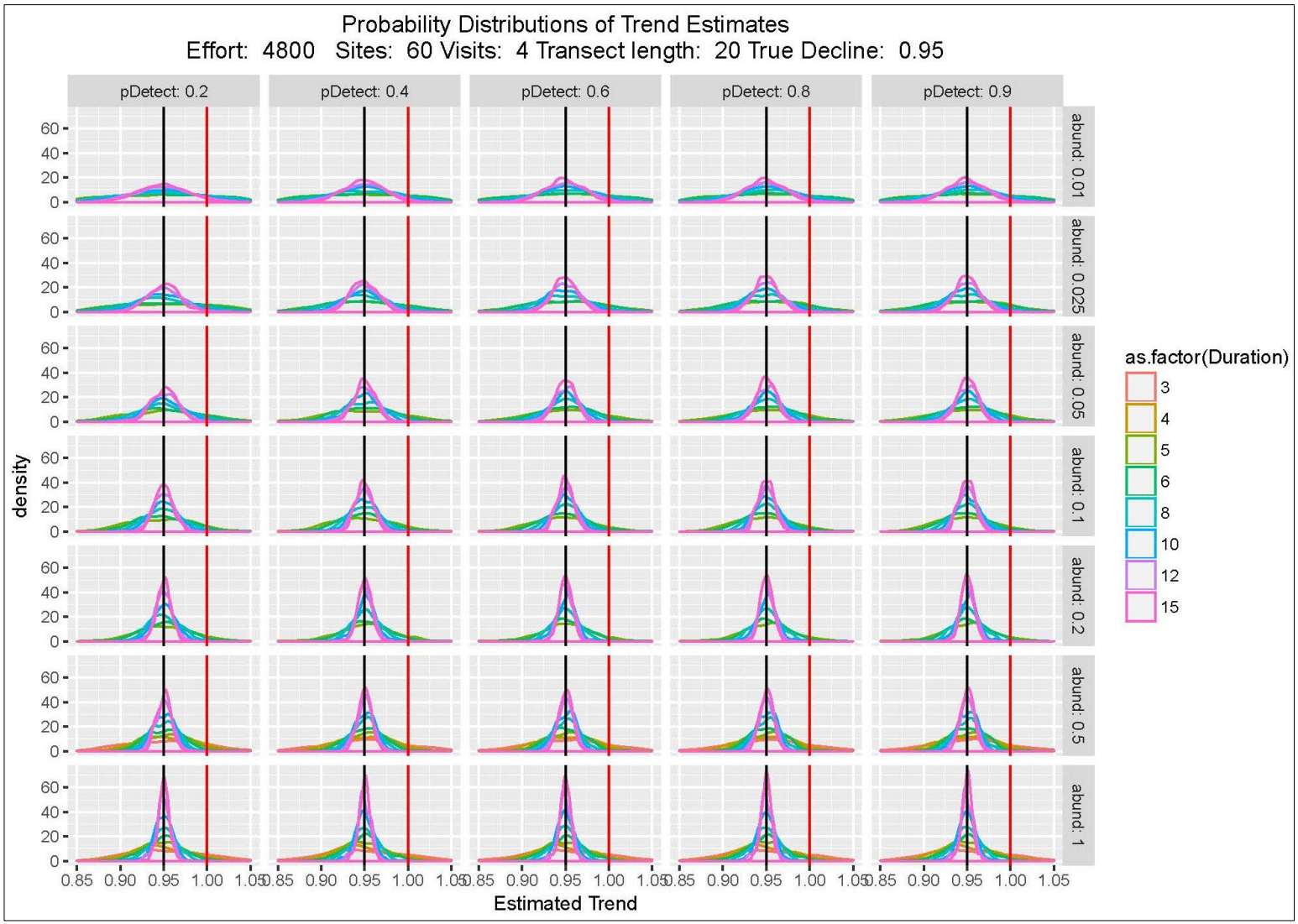


Figure A7-16. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 4800; Sites: 60; Visits: 4; Transect length: 20; and True Decline: 0.95.

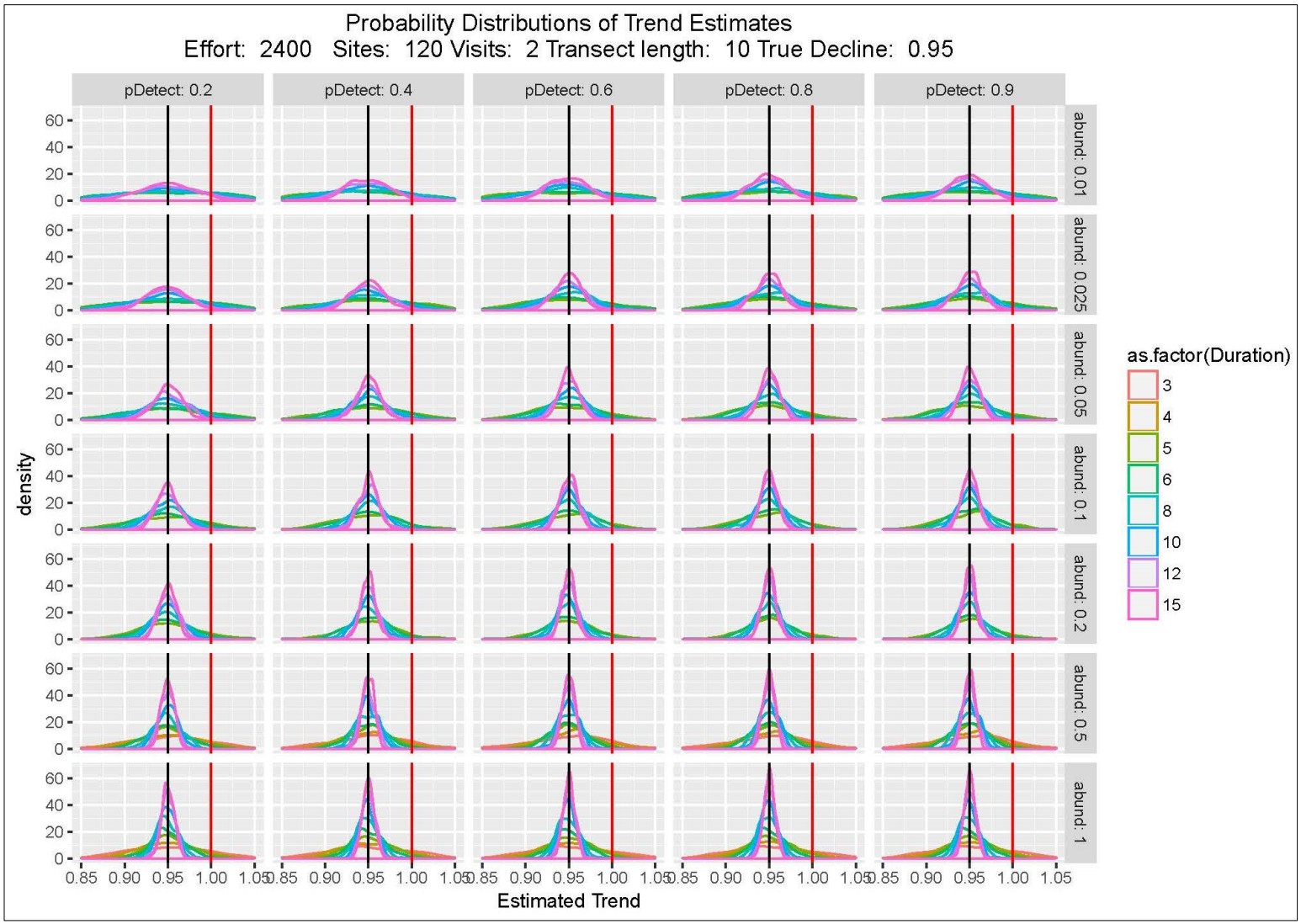


Figure A7-17. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 120; Visits: 2; Transect length: 10; and True Decline: 0.95.

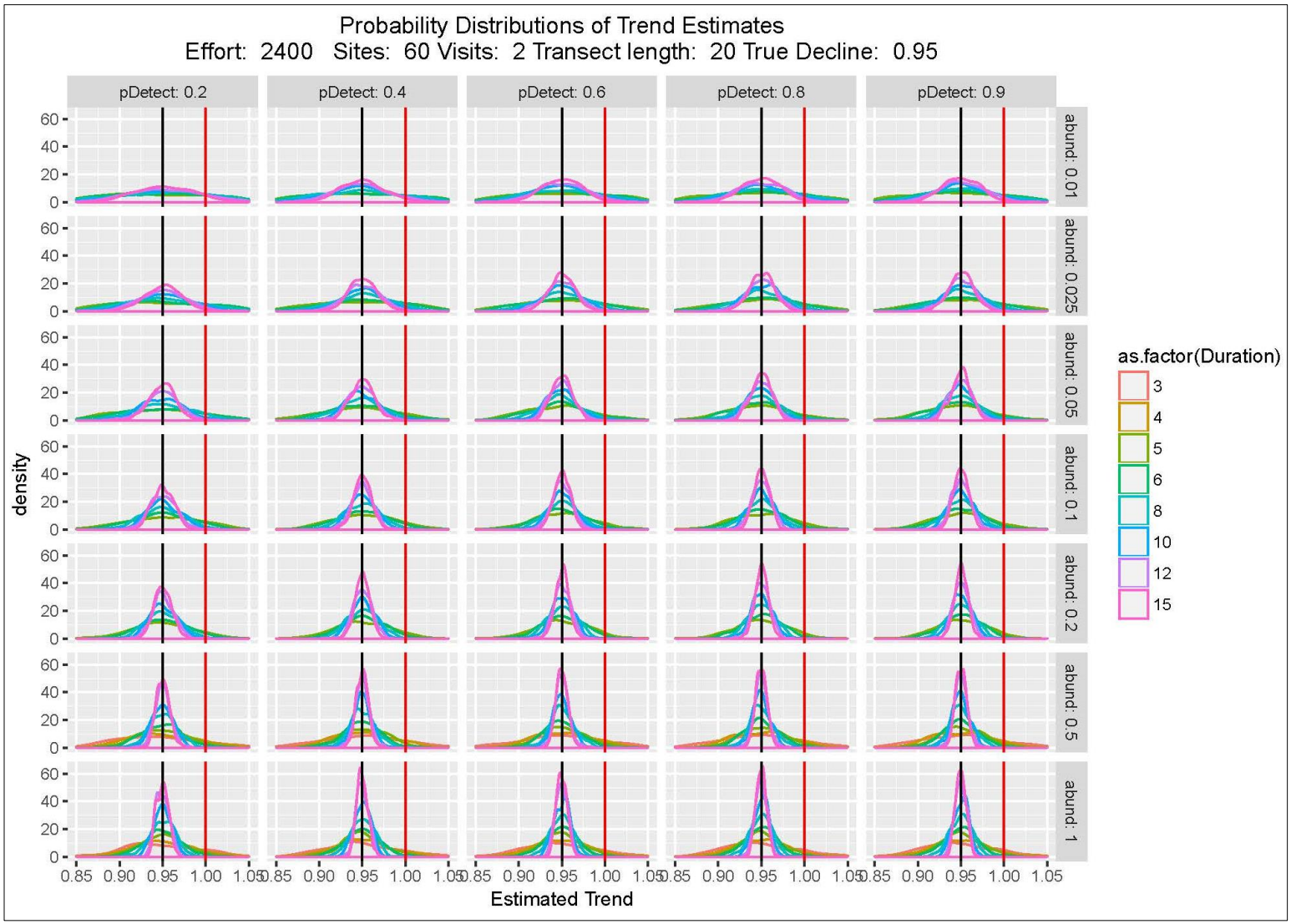


Figure A7-18. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 60; Visits: 2; Transect length: 20; and True Decline: 0.95.

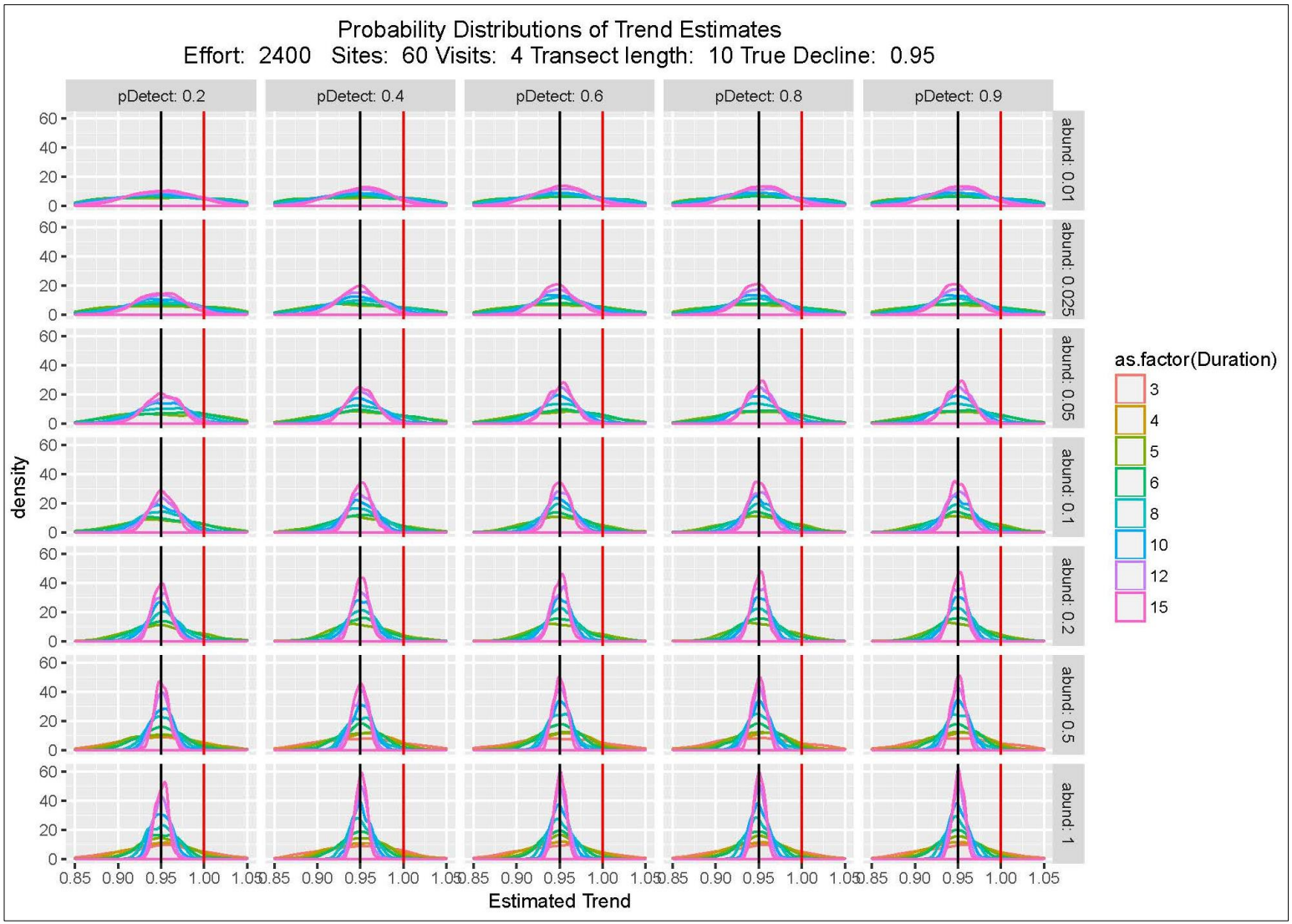


Figure A7-19. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 60; Visits: 4; Transect length: 10; and True Decline: 0.95.

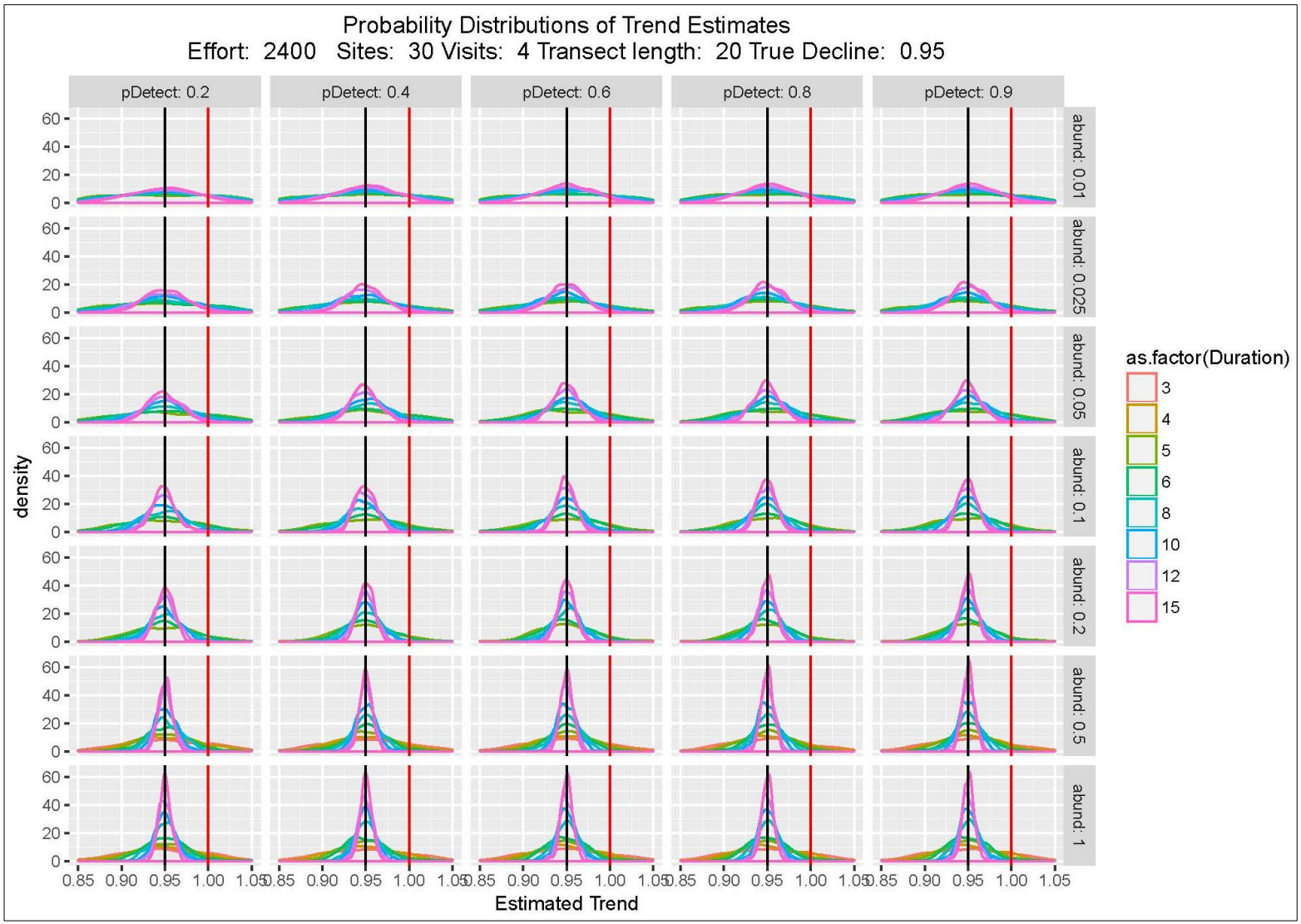


Figure A7-20. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 2400; Sites: 30; Visits: 4; Transect length: 20; and True Decline: 0.95.

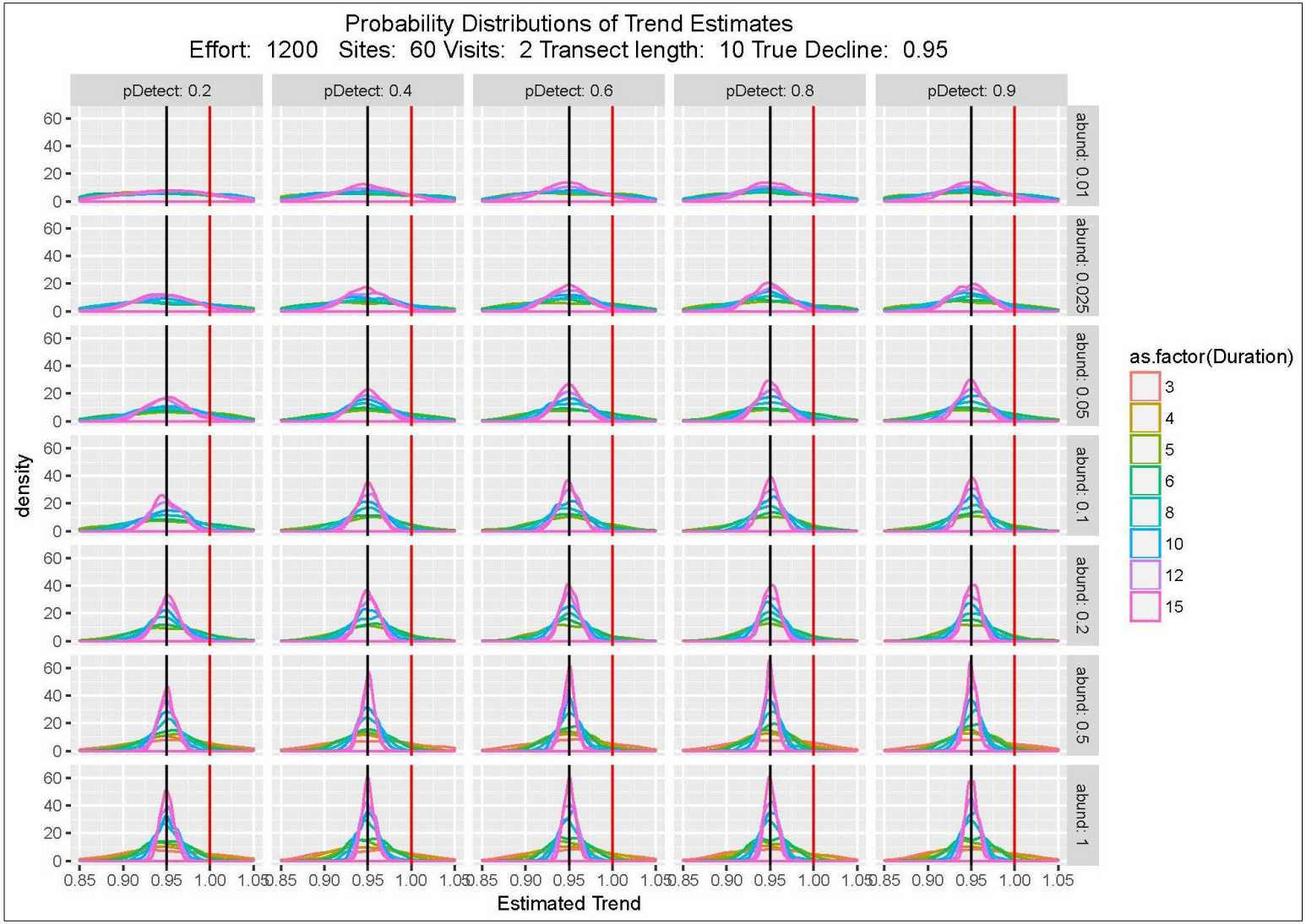


Figure A7-21. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of param estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 60; Visits: 2; Transect length: 10; and True Decline: 0.95.

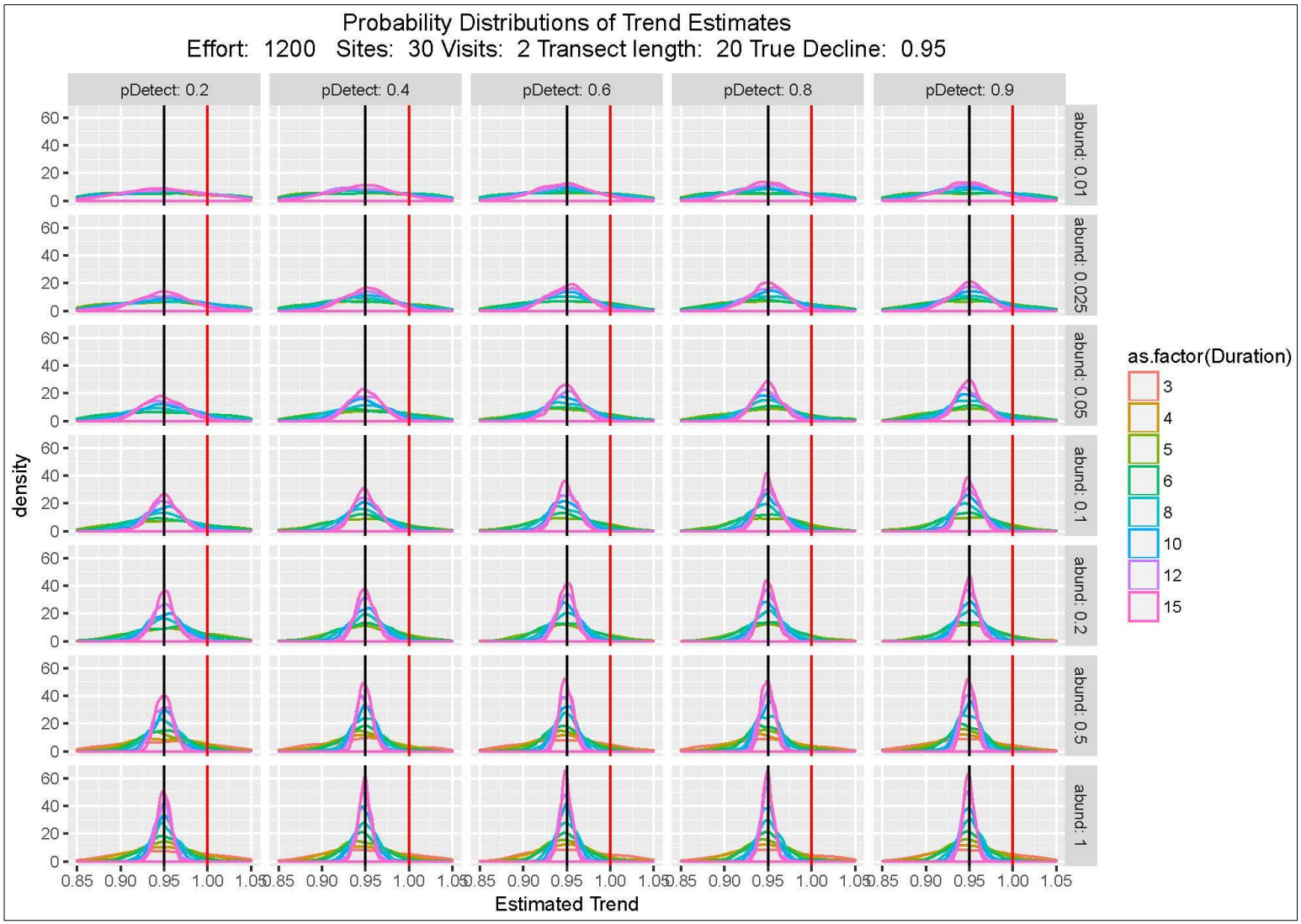


Figure A7-22. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 30; Visits: 2; Transect length: 20; and True Decline: 0.95.

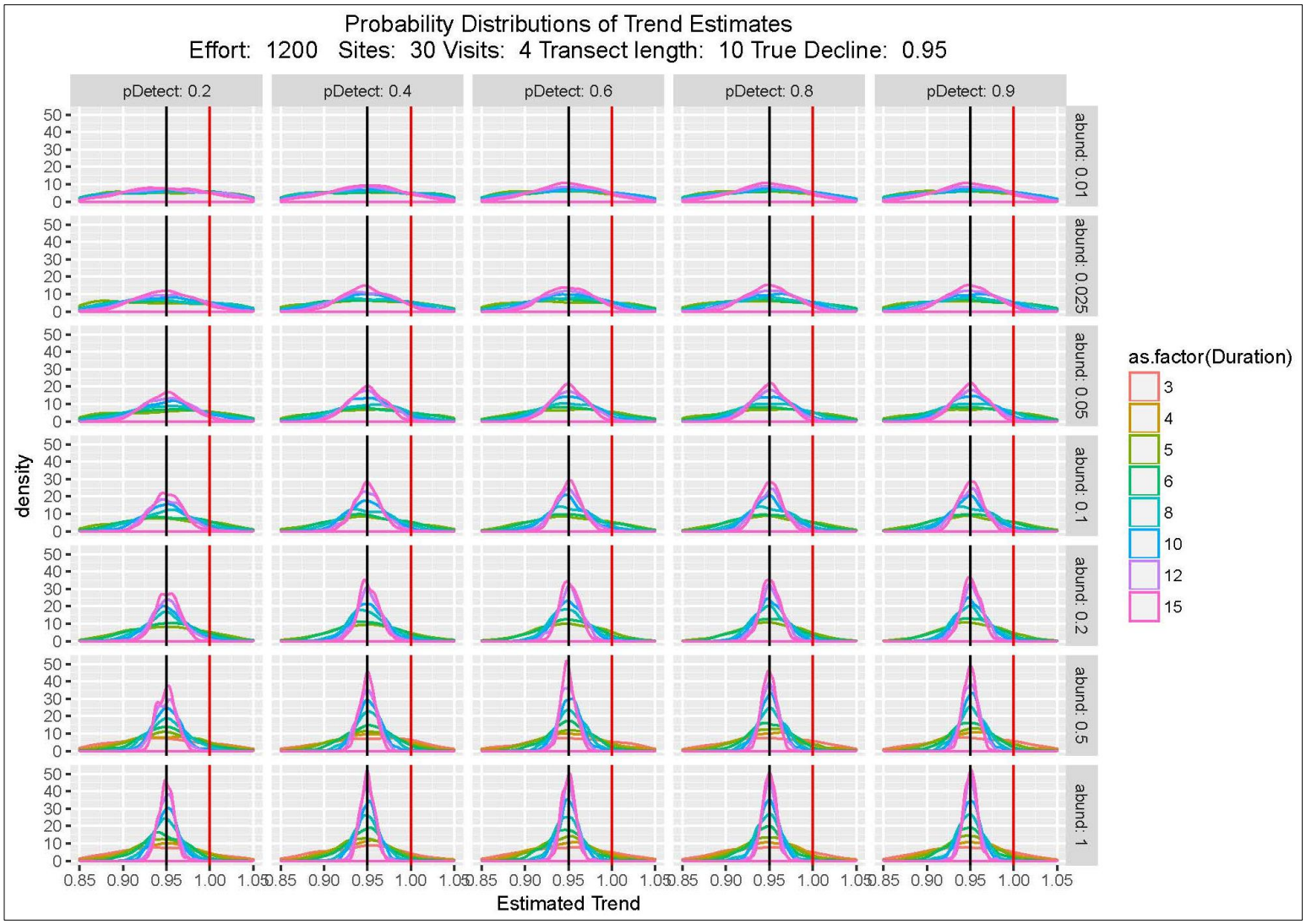


Figure A7-23. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 30; Visits: 4; Transect length: 10; and True Decline: 0.95.

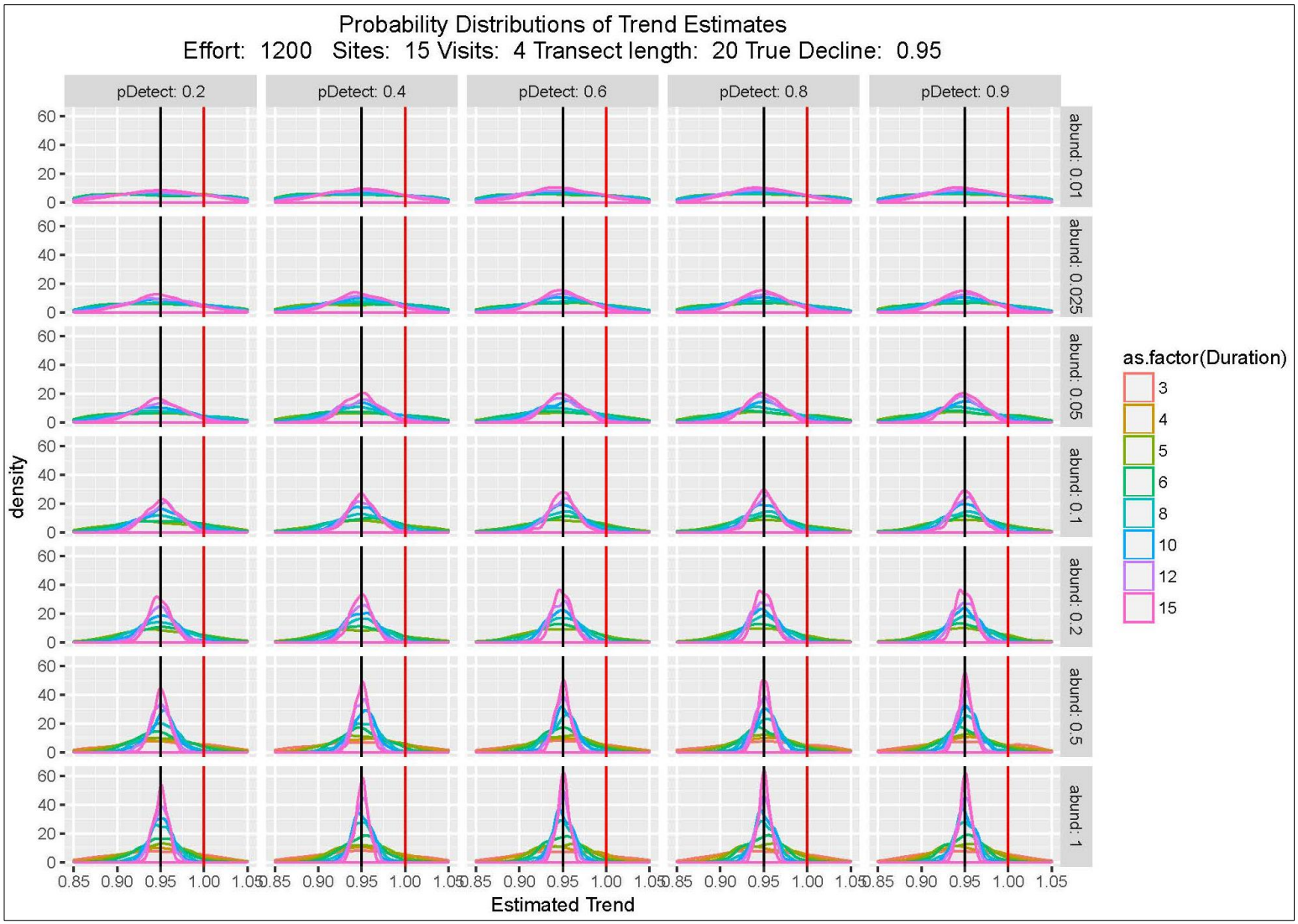


Figure A7-24. Graphs show a combination of total effort, transect length, the number of revisits, and true decline. Mean abundance at the start of the monitoring defines the rows of figures, and detection probabilities define the columns. Separate probability distributions of parameter estimates are presented for different durations of monitoring. Reference lines are provided for both the true trend (black) and trend = 1 (no change, red). Above, Probability Distributions of Trend Estimates. Effort: 1200; Sites: 15; Visits: 4; Transect length: 20; and True Decline: 0.95.

Appendix B. R code for the Single-Year Abundance Estimation Simulations

This code is also available as file StatusSimulationsFigs.R

```
setWindowTitle('CUPN CAB AHM status simulations')


# This code will run somewhat faster in Microsoft MRAN with
# pick one depending on which box it is running on...
#setwd('e:/CUPN/SimX')
#setwd('k:/CUPN/SimX')
#setwd('F:\\networks\\05_CUPN_CumberlandPiedmont\\Cave
Protocols\\Cave Aquatic Biota')
#setwd('n:/')
# setwd('n:/CUPN')
# setwd('i:/CUPN')
# setwd ('c:/temp')
#setwd('e:/CUPN/sim2400')


# keep working directory as a character object for use in
doParallel calls WD <-
'F:\\networks\\05_CUPN_CumberlandPiedmont\\Cave Protocols\\Cave
Aquatic Biota' setwd(WD)


pkgList <- c("reshape2", "plyr",
             "foreach", "doParallel",
             "Hmisc",
             "unmarked","AHMbook",
             "hSDM", # for inv.logit
             "ggplot2", "RColorBrewer" # graphics
             )
inst <- pkgList %in% installed.packages()
if (length(pkgList[!inst]) > 0)
install.packages(pkgList[!inst],dep=TRUE) lapply(pkgList,
library, character.only = TRUE)


## AHMbook not on CRAN (now it is so commented out)
#if (!'AHMbook'%in%inst)
install.packages(c("AHMbook","makeJAGSmask"),
#                                    repos =
"http://mikemeredith.net/R")
```

```
simreps <- 1000                 # Simulate and analyse 1000 data
sets for each parameter combo

tLength <- c(10, 20, 25, 30, 40, 50) # transect
lengths nVisit <- 2:6     # Levels of nrep factor

# Abundance values are in counts per m of
transect abund <- c(1, .2, .1, .05, .01)

# lambda will be abund *
tLength effort <- c(4800,
2400, 1200)


# sim combinations of effort, tLength, nVisit

bigT <- expand.grid(effort, abund, tLength, nVisit)
names(bigT) <- c('effort', 'abund', 'tLength',
'nVisit') bigT$nSite <- ceiling(bigT$effort /
bigT$tLength / bigT$nVisit) bigT$i <- 1:nrow(bigT) #
for later merging with long


# container for all results

estimates <- array(NA_real_, dim = c(2, simreps, nrow(bigT)))


# detection probabilities for each simulation  uniform [ 0.01
- 0.99] p <- array(runif(n=simreps*nrow(bigT),0.01,0.99),

                  dim= c(simreps,
                    nrow(bigT)))


# The simulations are wrapped up in a function that can be called
via foreach & dopar.

# Note that not all needed objects are explicitly passed to the
function as parameters.
```

```
# The function has (read-only) access to all data objects in
the calling environment,

# so only the iteration-specific value of Tsim is passed as a
parameter.


simFun <- function(Tsim) {
   # local results matrix, despite sharing the name of the
   much larger estimates]
   # object in the GlobalEnv
   estimates <- array(NA_real_, dim = c(2, simreps))
   for(ii in 1:simreps){       # Simulate and analyse simreps
      data sets Data <- simNmix(nsite=bigT$nSite[Tsim],
                     nvisit=bigT$nVisit[Tsim],
                     mean.lam = bigT$abund[Tsim] *
                     bigT$tLength[Tsim], mean.p=p[ii,Tsim],
                     show.plot = F)      # Generate data set
      umf <- try(unmarkedFramePCount(y = Data$C)) # Bundle data for
      unmarked if (!inherits(umf,'try-error')) {
         fm <- try(pcount(~1 ~1, umf, mixture='P', engine='C'))
         # Fit model
         if (!inherits(fm,'try-error')) estimates[,ii] <- coef(fm)
                                                              #
         Save estimates
      } # if !inherits umf
   }  # for i in simreps
   # save estimates object in case of reboot before all runs are
   completed
   # don't want all objects called "estimates" so construct
   unique name eName <- paste('Est2_',Tsim,sep='')
   assign(eName,estimates)
   # explicit path because doParallel doesn't necessarily use
   current working directory
   save(list=eName,file=paste(WD,'/',eName,'.Rdata',
   sep='')) return(estimates)
} # bottom simFun


registerDoParallel(cores=7) # YMMV, but for 4 core 8 thread i7 I
use 7, for 8/16 xeon I use 14 or 15


# in case of reboot/failure, this can be restarted by changing
the indices 1:nrow(bigT)
# then loading the individual Est2*.Rdata files
```

```
# wrap in system.time() to report elapsed user time
system.time(Estimates <- foreach(i=1:nrow(bigT),
.combine=rbind,
.inorder=TRUE,
                    .packages=c("unmarked", "AHMbook")) %dopar%
                    simFun(i)
          )

stopImplicitCluster() # just in case...
# wheeee!


########################################


 # look at the tiny corner of the resulting
  object Estimates[1:20,1:10]



# In theory, because .inorder=TRUE, Estimates should be in the right
order (by i or row bigT)
# In paractice, not so much.   So these 2 rows are commented out:
# estimates[1,,] <- exp(Estimates[seq(1,299,by=2),])
# estimates[2,,] <- inv.logit(Estimates[seq(2,300,by=2),])
```

```
# and replaced by a loop pulling the individual .Rdata files created
in simFun
# {defensive coding of simFun to write to external files pays off!}
# yeah, for loops are poor style, but when reading/loading files,
that doesn't matter, and
# note that the full estimates object in GlobalEnv is pre-
defined, so this does
# not grow an object see: R Inferno Circle 2
http://www.burns-
stat.com/pages/Tutor/R_inferno.pdf for (i in
1:nrow(bigT)) {
   eName <- paste('Est2_',i,sep='')
   load(paste(WD,'/',eName,'.Rdata',se
   p=''))
   estimates[1,,i] <- exp(get(eName)[1,])    # backtransform from
   log scale (Poisson abundance)
   estimates[2,,i] <- inv.logit(get(eName)[2,]) # back transform
   from logit scale (detection prob)
} # for i


save.image('temp.Rdat


a')


# For visualizations, we need to unwrap the estimates,
# and glue back on the corresponding parameter value
# tLine in estimates corresponds to row index in bigT
  # estiamted detection probs
  long0 <- melt(estimates[2,,],
  varnames=c('Sim','tLine')) names(long0)[3] <-
  'est.p'
  # estiamted abundances
  long1 <- melt(estimates[1,,],
  varnames=c('Sim','tLine')) names(long1)[3] <-
  'est.N'
  # detection probabilities from above
  long2 <- melt(p,
  varnames=c('Sim','tLine'))
  names(long2)[3] <- 'p'
```

```
  long <- merge(long1, long2,
  by=c('Sim','tLine')) long <- merge(long,
  long0, by=c('Sim','tLine'))


  # n.b. this merge reorders to character-based not numeric order
  for Sim & tLine!

  # putting them back into numeric
  order: str(long)

  long <- long[order(long$tLine,long$Sim),]


  #long$flag <- is.na(long$est.N)

  #aggregate(flag~tLine,data=long,FUN=mean)


# glue on parameter values from
bigT long$effort <-
bigT$effort[long$tLine]
long$tLength <-
bigT$tLength[long$tLine]
long$nVisit <-
bigT$nVisit[long$tLine] long$nSite
<- bigT$nSite[long$tLine]
long$abund <-
bigT$abund[long$tLine] long$Expect
<- long$abund * long$tLength


long$Est.p <- long$est.p

long$Est <- long$est.N # counts per transect

# estimate per 100m of stream

long$Est2 <- (long$Est / long$tLength) * 100

# as ratio to true (simulation parameter)
abundance long$Est3 <- long$Est / (long$tLength
* long$abund) #

# capped at 5x

long$Est4 <- pmin(long$Est3,5)
```

```
count(long, vars=c('tLength','abund','Expect'))


# semi-formatted labels
long$TL <- paste('Transect
length:',long$tLength) long$NV <-
paste(long$nVisit,'Visits')
long$NS <- paste(long$nSite,'Sites')


# quick & dirty graphs of real vs estimated for N and p as sanity
check
# that I really did get the right parameters with the right
estimates!
# Believe me: when they get randomly misaligned these figures make
that
# VERY obvious. Sad.
 ggplot(long, aes(x=Est, y=Expect, color=as.factor(abund))) +
    geom_point() + facet_wrap(~tLength)
 ggplot(long, aes(x=p, y=Est.p, color=as.factor(nVisit))) +
    geom_point() + facet_grid(abund~tLength) +
    geom_abline(slope=1,intercept=0)


#
long$samp_abund <- long$tLength * long$abund
long$SA <- paste('mean',long$samp_abund,'per
site')


biglong <- long
save(biglong,file='biglong.Rda
ta')


long$misfit <- is.na(long$Est)
long$Yikes <- (long$Est3 >
5)|(long$Est3<.2)
save(long,file='long.Rdata')
save.image('AbundSims.Rdata') #


##############################
# investigate fraction of models that don't converge or fit
# raw fraction by parameters
```

```
Oops <- aggregate(misfit ~ effort + tLength + nVisit + abund,
data=long, FUN= mean)


# for testing glmX function
# dsn <-
long[long$abund==.01&long$effort==1200&long$nVisit==2&long$tLen
gth==10,]


# probability of failure to return an estimate as a function of
(real, not estimated) p
glmX <- function(dsn) {
   lr <- glm(misfit ~ p, data=dsn,
   family=binomial) DF <-
   data.frame(p=seq(.01,.99,by=.02))
   DF$misfit <-
  predict(lr,newdata=DF,type='response')
  return(DF)
}
misfitByP <-
ddply(long,~effort+abund+tLength+nVisit,glmX,.progress='win')
misfitByP$TL <- paste('Transect length:',misfitByP$tLength)
misfitByP$NV <- paste(misfitByP$nVisit,'Visits')


#########
# also prob of estimate off by 5x or more
Oops2 <- aggregate(Yikes ~ effort + tLength + nVisit + abund,
data=long, FUN= mean)
Oops <- merge(Oops, Oops2,
by=c('effort','tLength','nVisit','abund'),all=TRUE)
```

```
Oops$Yikes <- Oops$Yikes * (1 - Oops$misfit)

########################################
```

Appendix C. R code for the Single-Year Abundance Estimation Simulations

This code is also available as file TrendSimsFigs.R

```
Y2Ysd <- 0.1 # s.d. of year to year multiplicative
variability setWindowTitle('CUPN CAB AHM trend
simulations')


# set the number of cores for registerDoParallel here
nCores <- 14  #YMMV, but for 4 core 8 thread i7 I use 7, for 8/16
xeon I use
14 or 15
# This code will run somewhat faster in Microsoft MRAN with Intel MKL
# which are, in fact, on the NPS approved software list!



# This set of simulations sets up the Txx set of parameter
combinations.
# Then for each record in Txx, it generates simreps simulated
datasets
# using those parameters, with each dataset composed of
# nSite sites * nYears years, with lambda (Poisson mean per site)
decreasing
# by Decline (multiplicative) per year from lambda (year 1) = abund.


# Working directory set both here and in function for foreach
parallel, so stored as object WD
WD <-
'F:\\networks\\05_CUPN_CumberlandPiedmont\\Cave Protocols\\Cave
Aquatic Biota\
# WD <- 'F:\\networks\\05_CUPN_CumberlandPiedmont\\Cave
Protocols\\Cave Aquatic Biota\\simZ/fill'
#WD <- 'e:/CUPN')
#WD <- 'n:/'
#WD <- 'n:/CUPN'
#WD <- 'n:/sim'
#WD <- 'i:/CUPN'
setwd(WD)


# load packages, installing from CRAN if necessary
pkgList <- c("reshape2", "plyr", "foreach",
"doParallel",
```

```
              "Hmisc",
              "unmarked","AHMbook",
              "hSDM", # for inv.logit
              "ggplot2", "RColorBrewer" # graphics
              )
inst <- pkgList %in% installed.packages()
if (length(pkgList[!inst]) > 0)
install.packages(pkgList[!inst],dep=TRUE) lapply(pkgList,
library, character.only = TRUE)



########################################
# sim 2 specified combinations of transect length (affecting lambda),
revisit number, and thus nsites
# each can be subset for running parts of interest, or
different hunks separately
# on different machines.


# Define simulation settings and arrays for sim results
simreps <- 500                 # Simulate and analyse 500 data sets


# tLen <- c(10,20,25,30,40,50)  # transect
lengths tLen <- c(10,20)      # transect
lengths
#nreps <- 4
nreps <- c(2,4)             # Levels of nrep factor


monYears <- c(3,4, 5, 6, 8, 10, 12, 15)   # numbers of years
for different trend tests
nYears <- max(monYears)           # max number of years of
trend monitoring
```

```
# Abundance values are in counts per m of transect
# lambda will be abund * tLength
abund <- c(1, .5, .1, .2, .05, .025, .01)
effort <- c(1200, 2400, 4800)
detects <- c(.2, .4, .6, .8, .9)
# rates of (multiplicative) decline per year
decline <- c(.90, .95, 1) # 10% and 5% per year, als no trend,
but that hasn;'t been run


# dataframe of all top-level parameter
combinations Txx <- expand.grid(tLen, nreps,
abund, decline, effort)
names(Txx) <- c('tlength','nVisit','abund', 'decline',
'effort') Txx$nSite <- ceiling(Txx$effort / Txx$tlength
/ Txx$nVisit) Txx$xx <- Txx$nSite * Txx$nVisit
Txx$i <-
1:nrow(Txx)
head(Txx)


save(Txx,file='Txx4_500.Rdata')


# loop over Txx combinations of transect lengths, revisits,
abundances per m at time==0,
# total effort, and rates of decline
#
# for each combination, generate simreps simulations at each
detection probability
# for each simulated dataset, estimate temporal trend with each
number of years in monYears
# save values in estimates


# Obs is a matix of nSites * monYears rows and nVisit columns
#


# The simulations are wrapped up in a function that can be called
via foreach & dopar.
# Note that not all needed objects are explicitly passed to the
function as parameters.
# The function has (read-only) access to all data objects in
the calling environment,
# so only the iteration-specific value of Tsim is passed as a
parameter.
```

```
# note that there is an alternate version of this simFun that
vectorizes more to reduce lops,

# at the cost of much more memory, as all simreps datasets are
created at once.
simFun <- function(Tsim) {
   # This version saves one estimates array per Tsim
   estimates <- array(NA_real_, dim = c(12,     # {abund0,
   abund_slope, det} *
   {est, lci, uci, p}
                                        simreps,
                                        length(detects
                                        ),
                                        length(monYear
                                        s)
                                        ))


   # for each site, covariate of Year <- 0:(nYears-1) and lambda
   as Poisson mean for that year
   Year <- rep(0:(nYears-1), times=Txx$nSite[Tsim])
   Lambdas <- (Txx$abund[Tsim] * Txx$tlength[Tsim]) *
   Txx$decline[Tsim]^(0:(nYe ars-1))


   for(i in 1:simreps){        # Simulate and analyse simreps
     data sets if (i%%10==0) print(Txx[Tsim,])
     cat("*** Simrep number", i, "***\n")
```

```
# Now (multiplicative) year to year variation with
sd=0.05 Lambdas2 <- Lambdas *
rnorm(nYears,1,sd=Y2Ysd)

N <-
rpois(Txx$nSite[Tsim]*nYears,rep(Lambdas2,times=Txx$nSite[Tsim
])) # actual number

for (pp in 1:length(detects)) { # loop over detection probs
                                                    currently 5

  # generate observations

  Obs <-
  matrix(data=rbinom(length(N)*Txx$nVisit[Tsim],size=rep(N,each=T
  xx

  $nVisit[Tsim]),prob=detects[pp]),

              ncol=Txx$nVisit[Tsim], byrow=TRUE)

  # fit models with varying number of years

  for (mY in 1:length(monYears)) {   # currently 6

    umf <- try(unmarkedFramePCount(y = Obs[Year<=monYears[mY],],

                                siteCovs=data.frame(Year=Year[Year
                                <=mon Years[mY]]))) # Bundle data
                                for unmarked

    print(system.time(fm <- try(pcount(~1~Year,umf))))     #
    currently called 30x per sim

    if (!inherits(fm,'try-
      error')) { out <-
      summary(fm)

      confint(fm,type='state',method='normal')

      # estimates 1:3 are coefficients for state, slope,
      detection,

      #          4:6 are lci for state, slope, detection,

      #          7:9 are uci for state, slope, detection,

      #          10:12 are p for state, slope, detection
      estimates[1:3, i, pp, mY] <- exp(coef(fm)) # Save
      estimates on linear scale

      estimates[4:5, i, pp, mY] <-
      exp(confint(fm,type='state',method='normal')[,1])
      estimates[7:8, i, pp, mY] <-
      exp(confint(fm,type='state',method='normal')[,2])
      estimates[c(6,9), i, pp, mY] <-
      inv.logit(confint(fm,type='det', method='normal'))

      estimates[10:11, i, pp, mY] <-
      out$state[,4] estimates[12, i, pp, mY]
      <- out$det[,4]


    } # bottom if !inherits(fm,try-error)


  } # bottom for (mY number of years
```

```
    } # bottom pp different detection probs
  } # bottom for i
  simreps setwd(WD)

  sName <-
  paste('estXXX',Tsim,sep='.')
  assign(sName,estimates)

  # save results to a file also in case processing gets
  interrupted
  save(list=sName,file=paste('estXX5',Tsim,'Rdata',sep='.'
  )) return(list(Tsim,estimates))
} # bottom function simFun



registerDoParallel(cores=nCores)
stuff <- foreach(i=1:nrow(Txx), .combine=rbind, .inorder=FALSE,
.packages= "unmarked") %dopar% simFun(i)
stopImplicitCluster()


save.image('TrendSimRaw.Rdata')
# if restarting:
# load('TrendSimRaw.Rdata')


# reload from parts, or graph rate of
completion DoNotRun <- function() {
getwd()
```

```
setwd(WD)
glob2rx('estXX5.*.Rdat
a')


outfiles <- list.files("."
,pattern="^estXX5\\..*\\.Rdata$") fileinfo <-
file.info(outfiles,extra_cols=FALSE) fileinfo$name <-
outfiles
nc <- nchar(fileinfo$name)
fileinfo$Txx <-

as.numeric(substr(fileinfo$name,8,nc-6)) fi <-

fileinfo[,c(7,8,1,4)]


library(ggplot2)
fig0 <- ggplot(data=fi,aes(x=Txx,y=mtime)) + geom_point() +
xlim(0,72) + geom_vline(xintercept=72)
fig0 + geom_smooth()


 fig1 <- ggplot(data=fi,aes(x=mtime,y=Txx)) + geom_point() +
        ylim(0,72) + geom_hline(yintercept=72)
fig1 + geom_smooth()

fi$Txx[order(fi$mtime
)]
fi$Txx[order(fi$Txx)]


} # bottom DoNotRun


##############################
          # estimates 1:3 are coefficients for state, slope,
          detection,
          #          4:6 are lci for state, slope, detection,
          #          7:9 are uci for state, slope, detection,
          #          10:12 are p for state, slope, detection



# stuff is a list of length 2 * nrow(Txx), with the returned
simulation data arrays as the
# 2nd half of the
objects Offset <-
nrow(Txx) uncube <-
function(z) {
```

```
  cube <-
  stuff[[z+Offset]]
  mcube <- melt(cube)

  names(mcube) <-
  c('Att','Sim','pp','mY','value')
  mcube$tlength <- Txx$tlength[z]

  mcube$nVisit <-
  Txx$nVisit[z] mcube$abund
  <- Txx$abund[z]
  mcube$decline <-
  Txx$decline[z] mcube$effort
  <- Txx$effort[z]
  mcube$nSite <- Txx$nSite[z]
  mcube$xx <- Txx$xx[z]
  return(mcube)

}


BigB <-
mdply(1:nrow(Txx),uncube)
str(BigB)

BigB$Attribute <- factor(BigB$Att,

                      labels=c('estAbund','estSlope','estDet
                              ect',
                              'lciAbund','lciSlope','lciDete
                              ct',
                              'uciAbund','uciSlope','uciDete
                              ct',
                              'sigAbund','sigSlope','sigDete
                              ct'))



BigB$Duration <-
monYears[BigB$mY] BigB$pDetect
<- detects[BigB$pp]
```

```
#save(BigB,'BigB.Rdata

') Big <-

BigB[,c(7:16,3,6)]



Big2 <- reshape2::dcast(Big,
                        tlength+nVisit+nSite+abund+decline+effort+Du
                        ration+ pDetect+Sim~Attribute,
                        value.var='value')


# flags for when slope confidence intervals don't include true slope
(decline) Big2$DetUp <- (Big2$uciDetect < Big2$pDetect)
Big2$DetDn <- (Big2$lciDetect > Big2$pDetect)

Big2$TrendUp <- (Big2$uciSlope <
Big2$decline) Big2$TrendDn <-
(Big2$lciSlope > Big2$decline)


Big2$powerSlope05 <- (Big2$sigSlope <
.05) Big2$powerSlope10 <-
(Big2$sigSlope < .1)



# performance pooled across sims
Stat <- aggregate(cbind(estSlope, TrendUp, TrendDn, sigSlope,
powerSlope05,
                        powerSlope10,   estDetect,   DetUp,   DetDn,
                        sigDetect)~
                        tlength+nVisit+nSite+abund+decline+effort+p
                        Detect+ Duration,
                        Big2, FUN=mean)
str(Stat)
Stat$cover <- 1 - Stat$TrendUp - Stat$TrendDn




# check for how many models failed to converge
 ss <-
                  count(Big2,c('tlength','nVisit','nSite'
                  ,'abund','decline',
                  'effort','pDetect','Duration'))
yesFit <-
count(Big2[!is.na(Big2$estSlope),],c('tlength','nVisit','nSite'
,'abund', 'decline',
```

```
                  'effort','pDetect','Duration'))
# what were the simulations that
failed?
Big2[is.na(Big2$estSlope),1:10]


save.image('TrendSim.Rdata')

# If not run in same session as TrendSims.R, run this block
of code: DoNotRun <= function() {
setWindowTitle('CUPN CAB AHM trend simulations')


# keep working directory as a character object for use in
doParallel calls WD <-
'F:\\networks\\05_CUPN_CumberlandPiedmont\\Cave Protocols\\Cave
Aquatic Biota' setwd(WD)


pkgList <- c("reshape2", "plyr",
             "Hmisc",
             "ggplot2", "RColorBrewer" # graphics
             )
inst <- pkgList %in% installed.packages()
if (length(pkgList[!inst]) > 0)
install.packages(pkgList[!inst],dep=TRUE) lapply(pkgList,
library, character.only = TRUE)


load('TrendSim.Rdata')
```

```
# probably could get by with just biglong:
# load('biglong.Rdata')


} # bottom DoNotRun reloading

code objects()

##############################


# create reference line dataset at 50% decline
# .5 = decline^T50 so log(.5) = log(decline)*T50     T50 =
log(.5) / log(decline)
# faceting by abund &
decline abundX <-
unique(Stat$abund) decX <-
unique(Stat$decline)
refLines <- expand.grid(abundX,decX)
names(refLines) <- c('abund','decline')
refLines$X <- log(.5) /
log(refLines$decline) refLines$X2 <-
log(.75) / log(refLines$decline)


str(BIG)
Stat_l <- reshape2::melt(Stat,
              id.vars=c('tlength','nVisit','nSite','abund',
                        'decline','effort','pDetect','Durat
              ion'),
              measure.vars=c('powerSlope05','powerSlope10'
              ), variable.name='Alpha',
              value.name='Power',
              factorsAsStrings =
              TRUE)
names(Stat_l)[9:10] <- c('Alpha', 'Power')
Stat_l$Alpha <-
as.factor(paste('.',substr(as.character(Stat_l$Alpha),11,12),
sep=''))


BIG$Alpha <-
as.factor(paste('.',substr(as.character(BIGat_l$Alpha),11,12)
,sep=''))
```

```
Stat$Abundance <- Stat$abund * 10
Stat_l$Abundance <- Stat_l$abund
* 10


# loop over pages by effort, nVisit nSite (tlength)


if (!dir.exists("figs")) dir.create("figs")
setwd("figs")


count(Stat,vars=c('effort','nVisit','nSite','tlength'))
dummy <-
expand.grid(unique(Stat$nVisit),unique(Stat$tlength),unique(Stat
$effort))
names(dummy) <- c("nV", "tl", "eff")
dummy <- dummy[order(-dummy$eff,dummy$nV,dummy$tl),]


#for (eff in unique(Stat$effort)) {
#   for (nV in unique(Stat$nVisit)) {
#     for (nS in unique(Stat$nSite)) {


 powerFig <- function(eff, nV,
   tl) { nS <- eff / nV / tl
   cat(eff,nV,nS,tl,'\n') # 30
   pages
   h1 <- paste("Effort: ", eff, "    Sites: ", nS,
               "Visits: ", nV, "Transect length: ",tl,
            '\nAbundances per 10m')
   pName <- paste('powerFig_', eff, '_', nS, '_',
   nV,sep='') junk <- Stat[Stat$effort==eff &
```

```
                Stat$nVisit==nV
                &
                Stat$tlength==t
                l,]
    junk_l <- Stat_l[Stat$effort==eff &
                Stat$nVisit==nV
                &
                Stat$tlength==t
                l,]
    if (nrow(junk)>6) {
      powFig <- try(ggplot(junk_l,
                           aes(x=Duration, y=Power,
                           color=as.factor(pDetect)))
                           +
                  geom_line(size=1) +
                  facet_grid(Abundance~decline+Alpha,
                  labeller=label_both) +
                  geom_vline(aes(xintercept=X),data=refLines,color='re
                  d') +
                  geom_vline(aes(xintercept=X2),data=refLines,color='b
                  lack') + ylab('Power to Detect at Given Alpha') +
                  xlab('Monitoring Duration
                  (Years)') + xlim(1,15) +
                  theme(plot.title = element_text(hjust =
                  0.5)) + ggtitle(h1))
      if (!inherits(powFig,'try-
         error')) { print(powFig)
         ggsave(paste(pName,
                '.png',sep=''),powFig,device='png',
               height=7.5, width=10, units='in')
    return(powFig)
    } # if !inherits(powFig05)
    } # bottom if nrow(junk)

} # bottom function powerFig
#     } # bottom for nS
#   }  # bottom for nV
#}   # bottom for eff


powerFigures <- mlply(dummy,.fun=powerFig)
```

```
# powerFig(2400,2,10)

pdf(file =

'PowerFig.pdf',
 #    width=10, height=7,
     width=8, height=10,
     onefile=TRUE,
     title='CUPN CAB
     Fig10',
    paper='US') #
paper="USr") powerFigures
dev.off()

#######################################
# coverage figure
#   Stat$cover is fraction of CIs that include true value

 coverFig <- function(nV, tl,
   eff) { nS10 <- eff / nV / 10
   nS20 <- eff / nV / 20


   cat(eff,nV,tl,'\n') # 30 pages
   h1 <- paste("Effort: ", eff, "Transect
              length: ",tl, '\nAbundances per
              10m',
              "\n  Sites: ", nS10, "Visits: 2",
             "                                          Sites: ",
             nS20, "Visits:
   4") junk <-
   Stat[Stat$effort==eff&
               Stat$tlength==tl,]
```

```
  if (nrow(junk)>6) {
        coverFig <- try(ggplot(junk,
                    aes(x=Duration, y=cover,
                    color=as.factor(pDetect))) + geom_line(size=1)
                    +
                    facet_grid(abund~decline+nVisit,
                    labeller=label_both) +
                    geom_hline(yintercept=.95,color='black') +
                    ylab('Coverage of 95% Confidence Intervals') +
                    xlab('Monitoring Duration (Years)') +
                    xlim(1,15) +
                    theme(plot.title = element_text(hjust =
                   0.5)) + ggtitle(h1))
        if (!inherits(coverFig,'try-
           error')) { print(coverFig)
           ggsave(paste('covFig_', eff, '_', tl,
           '.png',sep=''),coverFig, device='png',
                 height=7.5, width=6, units='in')
        } # if !inherits(coverFig)


      } # bottom if
      nrow(junk)
      return(coverFig)
} # bottom function coverFig


#     } # bottom for nS
#   }  # bottom for nV
#}   # bottom for eff


#coverFig(2400,2,10)


#cf1 <- coverFig(2400,2,10)



coverFigures <- mlply(dummy[dummy$nV==2,],.fun=coverFig)
```

```
# powerFig(2400,2,10)

pdf(file =

'coverFig.pdf',
 #    width=10, height=7,
     width=8, height=10,
     onefile=TRUE,
     title='CUPN CAB
     Fig11',
    paper='US') #
paper="USr") coverFigures
dev.off()


############
# coverage figure 2
#   Stat$tooHigh is fraction of CIs that are above true value
 tooHighFig <- function(nV, tl,
   eff) { nS10 <- eff / nV / 10
   nS20 <- eff / nV / 20


   cat(eff,nV,tl,'\n') # 30 pages
   h1 <- paste("Effort: ", eff, "Transect
              length: ",tl, '\nAbundances per
              10m',
              "\n  Sites: ", nS10, "Visits: 2",
```

```
            "                                          Sites: ",
            nS20, "Visits:
  4") junk <-
  Stat[Stat$effort==eff&
             Stat$tlength==tl,]


 if (nrow(junk)>6) {
       tooHighFig <- try(ggplot(junk,
                   aes(x=Duration, y=tooHigh,
                   color=as.factor(pDetect))) + geom_line(size=1)
                   +
                   facet_grid(abund~decline+nVisit,
                   labeller=label_both) +
                   geom_hline(yintercept=.025,color='black') +


                   ylab('Fraction of Confidence Intervals above
                   Simulation Slope') +
                   xlab('Monitoring Duration
                   (Years)') + xlim(1,15) +
                   theme(plot.title = element_text(hjust =
                  0.5)) + ggtitle(h1))
       if (!inherits(tooHighFig,'try-error'))
          { print(tooHighFig)
          ggsave(paste('tooHighFig_', eff,
          '_', tl,
          '.png',sep=''),tooHighFig,device='p
          ng',
                 height=7.5, width=6, units='in')
       } # if !inherits(coverFig)


      } # bottom if
      nrow(junk)
      return(tooHighFig)
} # bottom function coverFig


#     } # bottom for nS
#   }  # bottom for nV
#}   # bottom for eff


#tooHighFig(2400,2,10)


#cf1 <- coverFig(2400,2,10)
```

```
tooHighFigures <- mlply(dummy[dummy$nV==2,],.fun=tooHighFig)


# tooHighFig(2400,2,10)

pdf(file =

'tooHighFig.pdf',
 #    width=10, height=7,
     width=8, height=10,
     onefile=TRUE,
     title='CUPN CAB
     Fig12',
    paper='US') #
paper="USr") tooHighFigures
dev.off()


##############################################
############
# coverage figure 2
#   Stat$tooLow is fraction of CIs that are above

true value tooLowFig <- function(nV, tl, eff) {
```

```
  nS10 <- eff / nV /
  10 nS20 <- eff /
  nV / 20


  cat(eff,nV,tl,'\n') # 30 pages
  h1 <- paste("Effort: ", eff, "Transect
           length: ",tl, '\nAbundances per 10
           m',
            "\n  Sites: ", nS10, "Visits: 2",
          "                                          Sites: ",
          nS20, "Visits:
  4") junk <-
  Stat[Stat$effort==eff&
           Stat$tlength==tl,]


  if (nrow(junk)>6) {
       tooLowFig <- try(ggplot(junk,
                    aes(x=Duration, y=tooLow,
                    color=as.factor(pDetect))) + geom_line(size=1)
                    +
                    facet_grid(abund~decline+nVisit,
                    labeller=label_both) +
                    geom_hline(yintercept=.025,color='black') +


                    ylab('Fraction of Confidence Intervals above
                    Simulation Slope') +
                    xlab('Monitoring Duration
                    (Years)') + xlim(1,15) +
                    theme(plot.title = element_text(hjust =
                   0.5)) + ggtitle(h1))
       if (!inherits(tooLowFig,'try-
          error')) { print(tooLowFig)
          ggsave(paste('tooLowFig_', eff, '_', tl,
          '.png',sep=''),tooLowFig, device='png',
                height=7.5, width=6, units='in')
       } # if !inherits(coverFig)


     } # bottom if
     nrow(junk)
     return(tooLowFig)
} # bottom function coverFig


#    } # bottom for nS
#  }  # bottom for nV
```

```
#}   # bottom for eff


#tooLowFig(2400,2,10)


#cf1 <- coverFig(2400,2,10)



tooLowFigures <- mlply(dummy[dummy$nV==2,],.fun=tooLowFig)


# tooLowFig(2400,2,10)

pdf(file =

'tooLowFig.pdf',
 #    width=10, height=7,
     width=8, height=10,
     onefile=TRUE,
     title='CUPN CAB
     Fig12',
    paper='US') #
paper="USr") tooLowFigures
dev.off()
```

```
str(Stat)
with(Stat,table(abund,nVisi
t))


#################
# distributions of trend estimates
# estimate on X density on Y
# color by Duration
# facetted by abund and pDetect
# paged by effort, nVisit,

tLength str(BIG)

dummy2 <- expand.grid(unique(BIG$nVisit), unique(BIG$tlength),
                      unique(BIG$effort),
unique(BIG$decline)) names(dummy2) <- c("nV", "tl",
"eff", "dec")
dummy2 <- dummy2[order(dummy2$dec,-dummy2$eff,dummy2$nV,dummy2$tl),]


 detDistFig <- function(eff, nV, tl,
   dec) { nS <- eff / nV / tl
   cat(eff,nV,nS,tl,dec,'\n') #
   if (dec==0.9) {
     xl <- c(0.8,1.05)
   } else {
     xl <- c(0.85,1.05)
   } # if else dec==.9
   h1 <- paste("Probability Distributions of Trend Estimates\nEffort:
   ", eff, " Sites: ", nS, "Visits: ", nV,
             "Transect length: ",tl,"True Decline: ",dec)
   pName <- paste('pdfFig_', eff, '_', nV, '_', tl,
   '_',dec,sep='') junk <- BIG[BIG$effort==eff &
              BIG$nVisit==nV
              &
              BIG$tlength==tl
              &
              BIG$decline==de
              c,]
    tDistFig <-
           ggplot(junk,aes(estSlope,color=as.factor(Duration
```

```
            ))) + geom_density() +
            facet_grid(abund~pDetect,labeller=label_both) +
            xlim(xl) +
            geom_vline(xintercept=de
            c) +
            geom_vline(xintercept=1,color='red') +
            theme(plot.title = element_text(hjust =
            0.5)) + ggtitle(h1) +
            xlab("Estimated
    Trend") print(tDistFig)
    ggsave(paste(pName,
             '.png',sep=''),tDistFig,device='png',
             height=7.5, width=10, units='in')
  return(tDistFig)
 } # bottom function detDistFig


pdfFigures <- mlply(dummy2,.fun=detDistFig)



 pdf(file =
     'distribFig.pdf',
     width=10, height=7,
#     width=8,
     height=10,
     onefile=TRUE,
     title='CUPN CAB
     Fig7',
```

```
    paper='USr')# paper="US")
pdfFigures

dev.off()
```